Out of Work, Out of the Labour Force? Attachment, Search Effort and Participation Flows*

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Abstract

We document that in the UK the outflow rate of unemployed workers into inactivity is strongly procyclical and accompanied by a shift in the composition of unemployed workers towards those with higher labour market attachment. Using data from the UK Labour Force Survey, we show that the key determinant of labour market attachment among the unemployed—their propensity to reduce search effort during an unemployment spell—is whether a worker entered unemployed from inactivity or from losing their job. We further document that these differences in attachment are not accounted for by differences in search effort behaviour. Motivated by this empirical evidence, we set up a Diamond–Mortensen–Pissarides model with endogenous separations and heterogeneity in attachment among the non-employed to study the implications of this channel for unemployment dynamics. The model implies that countercyclical job separations have significant effects on the average degree of attachment among the unemployed, amplifying unemployment volatility by roughly 50 percent relative to a counterfactual where all unemployed workers remain attached. The increase in average attachment among the unemployed helps to account for the initial surge in unemployment at the onset of the Great Recession.

Keywords: *Labour force participation, Labour market attachment, Search effort, Unemployment*
JEL Codes: *E24, E32, J21, J64*

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1 Introduction

Economists and policymakers have long been interested in accurately measuring the degree of economic slack and understanding the causes of its cyclical variation. Until relatively recently the dominant view was that fluctuations in labour market slack could be explained almost entirely by cyclical fluctuations in labour demand, whilst labour supply was viewed as acyclical and therefore unimportant for understanding cyclical labour market dynamics. Yet a distinguishing feature of the two most recent large recessions across many advanced economies - the Great Recession in 2008 and the Covid-19 pandemic recession in 2020 - was a sizeable and persistent contraction in the size of the labour force. This led many researchers and policymakers to emphasise the importance of improving our knowledge of the role of cyclical changes in labour force participation rates for labour market slack over the business cycle.[1]

Recent developments in the theoretical literature have reflected this pivot towards understanding the cyclicality of labour supply, where there has been growth in the development of frameworks in the Diamond-Mortensen-Pissarides (DMP) frictional labour markets tradition featuring a labour participation margin.[2] However it has been shown to be challenging to ensure that these frameworks produce plausible cyclical behaviour in both labour market aggregates and flows that is consistent with the data.[3] Most of the earlier contributions in this literature focused on generating the correct co-movement in labour market aggregates, but often achieved this by introducing mechanisms which are inconsistent with evidence from micro-data on labour market flows. Although there are some important recent exceptions to this - notably Krusell et al. (2017) and Cairo et al. (2022) - a standard general equilibrium matching framework featuring labour force participation that is capable of matching empirically realistic labor force flows has yet to emerge.

In this paper we focus on the role of heterogeneity in labour force attachment among the unemployed for driving participation flows, particularly the outflows from unemployment. Throughout the paper we consider all non-employed workers as 'searchers', but where there is substantial heterogeneity in their search *effort*. From this perspective ac-

[1] For example see Bernanke (2012), Yellen (2014) and Bullard (2014), and more recently Bailey (2023) and Pill (2023).

[2] Examples include Tripier (2004), Haefke and Reiter (2006), Veracierto (2008), Shimer (2013), Krusell et al. (2017), Christiano, Trabandt and Walentin (2021), and Cairo et al. (2022). In environments featuring nominal rigidities there are also contribution by Galí et al. (2012), Speigner (2012), and Campolmi and Gnocchi (2016).

[3] New 'puzzles' have not only been quantitative in nature (linked to other well-known puzzles, such as the unemployment volatility puzzle), but rather *qualitative* in the sense that even generating the correct cyclicality of labour market aggregates like unemployment and labour force participation is non-trivial.

tive labour force participation is a statement about the relative search effort of a worker - whether their search effort e falls below some threshold $\underline{e}$ where a worker is statistically defined as economically inactive. This is consistent with recent evidence documenting that in practice many inactive workers are searching for new jobs and make up a non-negligible share of new hires (e.g. Faberman et al. 2022), as well as formal definitions of labour force status used in official surveys.[4] By 'labour market attachment' we are therefore referring to the propensity of an individual unemployed worker to *reduce* their search effort during an unemployment spell. Conditional on being unsuccessful in job search, workers who are more attached will search harder for longer.

The first part of the paper presents empirical analysis of labour market flows, attachment and search effort using data from the UK Labour Force Survey (LFS). Firstly, we revisit the evidence on the cyclicality of labour market flows in the UK, with a particular focus on worker flows in and out of the labour force, i.e. participation flows. We show that in the UK aggregate inflows into the labour market are broadly acyclical whereas outflows are procyclical, most notably among the unemployed. Similar to what Elsby et al. (2015) document for the United States, we illustrate that procyclicality in the outflows from unemployment is driven by compositional shifts in the unemployment pool during downturns towards groups of workers with higher attachment, notably: male, prime-aged, university educated workers who were previously employed. Moreover, we go further by formally providing evidence that, controlling for other worker characteristics, it is an unemployed worker's previous labour force status which is the strongest predictor of labour market attachment, which we proxy for with individual unemployment-to-inactivity (UN) transitions. In other words, workers who have entered unemployment directly from employment via job separation are much less likely to reduce their search effort during an unemployment spell such that they leave the labour force.

Additionally, in the absence of direct evidence on individual search effort in the LFS we adopt the approach in Barnichon and Figura (2015) to estimate individual search intensities in order to unpack whether there are differences in search effort conditional on previous labour force status which can account for the differences in degree of labour market attachment. The higher attachment (lower UN rate) among previously employed workers may simply reflect that these workers search harder and find jobs faster, and are therefore less likely to exit the labour force. We establish two key empirical facts about the distribution of search effort across individuals. First, as expected, we show that estimated

[4]For instance, the International Labour Organization (ILO) defines unemployed workers as being: (i) "without a job, have been actively seeking work in the past four weeks and are available to start work in the next two weeks", or (ii) "out of work, have found a job and are waiting to start it in the next two weeks".

search effort among the unemployed is significantly higher on average than among the inactive, consistent with the notion that labour force status is a reflection about individual search effort. Importantly, however, we do not find evidence that there are differences in the average level or cyclicality of search effort among the unemployed based on their previous labour force status. Taken together this evidence further suggests that differences in the attachment of previously employed versus previously inactive unemployed workers is driven by a genuine difference in their propensity to reduce their search effort over the course of an unemployment spell. These properties of the data play an important role in shaping the assumptions we make about the distribution of search intensity at the individual level.

After documenting the role of compositional effects in accounting for procyclical unemployment outflows and highlighting the importance of previous labour force status for attachment, we analyse the contribution of this particular mechanism for labour market fluctuations. To do this we extend a canonical DMP model with endogenous job separations to allow for heterogeneity in search effort among the non-employed (which determines labour force status), as well as heterogeneity in labour market attachment conditional on previous labour force status consistent with our empirical findings. We then calibrate the model and use it to explore the role of heterogeneity in labour force attachment by previous labour force status in accounting for the volatility in unemployment. Despite its simplicity, the resulting framework is able to replicate the correct cyclicality of all labour force flows we estimate in the data without relying on a combination of mechanisms or shocks to achieve this.[5] We show that the interaction between endogenous job separations and its impact on the composition of workers by attachment in the unemployment pool increases the volatility of unemployment by around 50%, despite the fact that in equilibrium a search pool with greater attachment dampens the volatility of job creation. Finally, we show that through the lens of the model this composition effect is important for capturing the initial rise in unemployment during the Great Recession.

Related literature. This paper seeks to bridge the empirical literature emphasising the importance of cyclical labour supply for labour market dynamics with a theoretical lit-

[5]The seminal contribution by Krusell et al. (2017) is able to replicate the cyclicality of labour market flows in a partial equilibrium setting due to the interaction of search frictions and wealth effects in the participation decision via a standard incomplete markets setup. When this is extended to general equilibrium (Krusell et al. 2020) they find that aggregate TFP shocks of the type typically used to assess the fit of search models with the data (e.g. Shimer 2005) generate counterfactual predictions for gross worker flows, and instead find that shocks to the job finding and separation margins are important in driving the observed cyclicality in labour market flow rates. Cairo et al. (2022) instead find they are able to match cyclical movements in flows conditional on a labour productivity shock via a combination of different persistence in home productivity among the inactive and unemployed, non-linear utility and rigid wages.

erature that seeks to incorporate participation flows into models of equilibrium unemployment with search & matching frictions. Additionally, we also bridge two branches of the theoretical literature by allowing for heterogeneous search intensity among the non-employed and defining non-participation relative to some exogenously chosen threshold, rather than via a discontinuous participation decision.

The flows-based approach to analysing the cyclical properties of the labour market we adopt in this paper follows key contributions such as Elsby, Michaels and Solon (2009), Fujita and Ramey (2009), Shimer (2012) and Elsby et al. (2019) using US data from the Current Population Survey (CPS), and Petrongolo and Pissarides (2008), Smith (2011) and Gomes (2012) using UK data. Earlier contributions in this literature have focused on the debate as to whether separations into unemployment (the EU rate) or transitions from unemployment to employment (the UE rate) are more important in accounting for unemployment dynamics in the data, and tended not to focus on the role of transitions into and out of the labour force. The relationship between cyclicality in labour market conditions and labour supply has been recognised at least since early work by Perry (1971) and Okun (1973), which documented a mild procyclicality of aggregate labour supply.[6] The seminal contribution emphasising the importance of the participation margin for cyclical labour market fluctuations is Elsby et al. (2015) in the context of the US. Our analysis shows that similar patterns hold for the UK labour market, notably the compositional shifts in the unemployment pool towards workers with higher attachment. We go further here in formally quantifying the relative importance of different worker characteristics for attachment, and emphasise the importance of previous labour force status in determining attachment.[7]

With regards to the theoretical literature, there have been many attempts at integrating a labour supply margin into standard DMP models. Notable early examples include Tripier (2004) and Veracierto (2008), however these frameworks feature incentives to participate that are linked to labour market tightness and therefore are strongly procyclical, to the extent that unemployment becomes counterfactually procyclical. Haefke and Reiter (2006) find that heterogeneity in the outside option can address this issue, whilst Shimer (2013) emphasises the role of wage rigidities in mitigating the rise in the value of participation during booms. A subset of the literature has also embedded similar environments into New Keynesian models to study the implications of the participation margin for mon-

[6] A brief overview of this literature is provided in Hobijn and Sahin (2021).

[7] In the CPS the question asking about previous activity asks about labour force status 12 months ago, in contrast to the UK LFS which just asks about previous labour force status and is cleaner on this dimension.

etary policy.[8] However none of these studies attempt to develop environments which aim to be consistent with the cyclical behaviour of labour market flows we observe in the micro-data.

There are several important exceptions to this. Firstly, Krusell et al. (2017, 2019) develop a rich environment where workers face idiosyncratic risk, incomplete markets, search frictions in the labour market and make a participation decision. Empirically realistic cyclicality in worker flow rates is generated by wealth heterogeneity and the associated compositional effects. This framework has also been used by Graves et al. (2023) to study the role of labour supply channels for the transmission of monetary policy and its implications for labour market flows. The most closely related paper to ours is Cairo et al. (2022) who first document the cyclicality of worker flows conditional on aggregate productivity shocks and subsequently develop a framework to explicitly match these facts. In the context of a standard discrete participation decision, they emphasise the importance of the participation margin being *countercyclical*, i.e. booms are times when households decide to send fewer workers to the labour force. To achieve this they rely on several model features including non-linear utility, substitutability between home and market goods, rigid wages, as well as additional assumptions. Relative to their environment, our simpler framework is able to qualitatively generate cyclical flows that are consistent with the data based on only on the inclusion of a single additional mechanism based on heterogeneity in labour force attachment among the unemployed which we first document empirically.

Finally, our model is closely related to another literature which has studied the implications of variable search intensity for labour market dynamics. Key contributions of this are Pissarides (2000), Shimer (2004), Mitman and Rabinovich (2015), Mukoyama et al. (2018) and Faberman et al. (2022). Our contribution relative to these papers is to allow for search intensity among the non-employed to be heterogeneous, where we then define labour force participation based on an exogenously determined threshold for search intensity, and we introduce a simple mechanism whereby labour market attachment depends on previous labour force status, which we show in the data is the key determinant of attachment.

Layout. The rest of the paper is structured as follows. In Section 2 we present evidence on participation flows and the labour market attachment. In Section 3 we present evidence on search effort and its relationship with previous labour force status in the

[8] Examples include Galí et al. (2012), Speigner (2012) and Campolmi and Gnocchi (2016). Erceg and Levine (2014) also study the implications of the participation margin for monetary policy, but do not model equilibrium unemployment using search & matching frictions.

context of attachment. Section 4 studies the implications of heterogeneity in labour force attachment for labour market dynamics. We set up a search and matching model with heterogeneous labour market attachment which is consistent with empirical evidence on labour market flows, heterogeneity in attachment among the unemployed, and evidence on job search. We then analyse the implications of empirically-consistent participation flows for unemployment volatility. Section 5 concludes.

2 Participation Flows and Labour Market Attachment

2.1 Revisiting the Role of Participation Flows

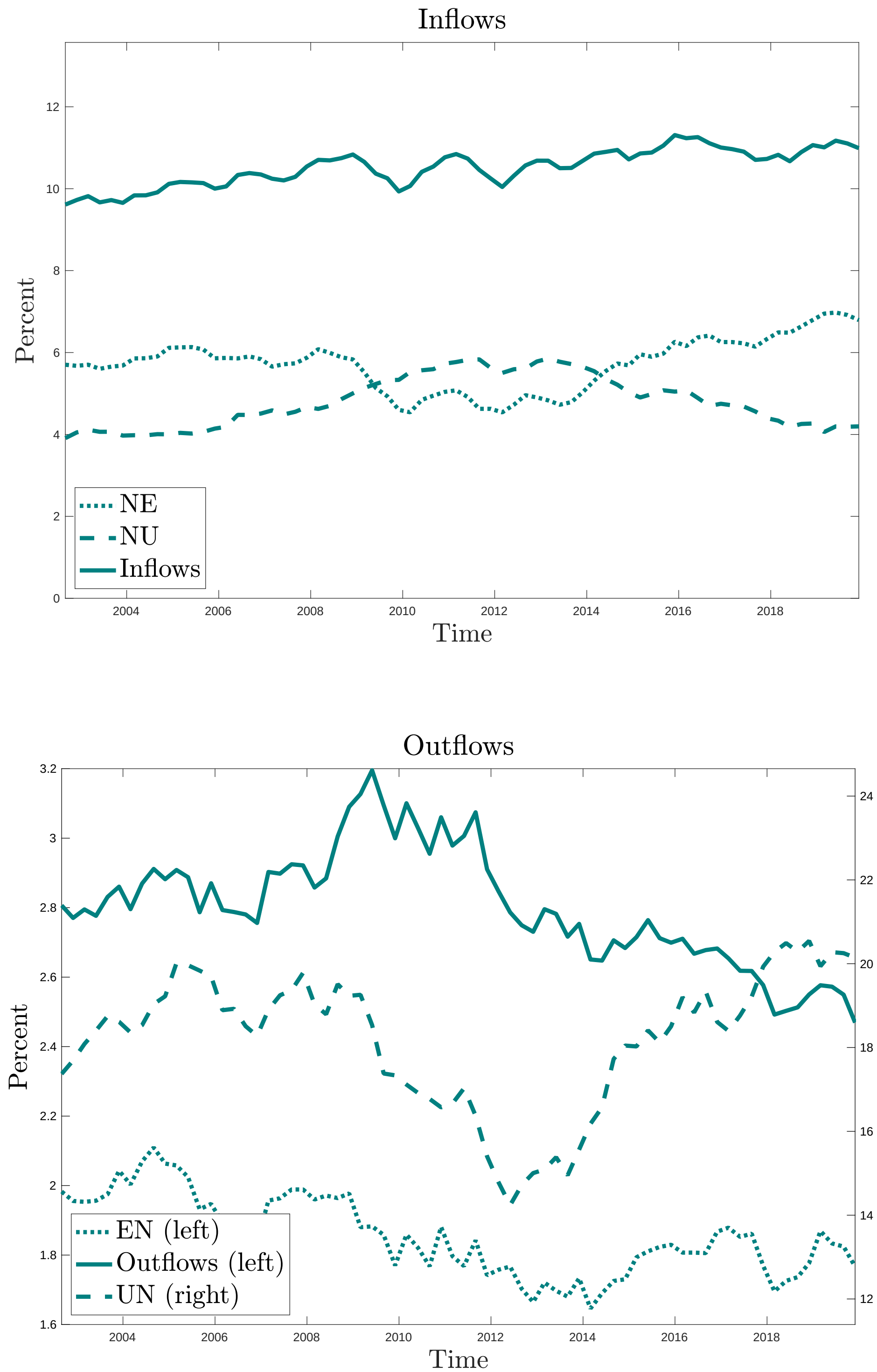
In this section we revisit the properties of labour market flows in the United Kingdom first documented by Smith (2011) and Gomes (2012), with a particular focus on flows into and out of the labour force, i.e. *participation* flows. We use data from the UK Labour Force Survey covering the period 2001Q1-2019Q4. For more details on the data and our sample construction see Appendix A.[9] We begin by outlining that whilst inflows into the labour force are acyclical, outflows from the labour force are comparatively cyclical - in particular highlighting that whilst the overall rate of outflows is countercyclical, giving rise to procyclical movements in participation, the rate at which unemployed workers exit the labour force is actually *procylcical*. We then illustrate the role of participation flows for labour market dynamics, emphasising the importance of the procyclical outflow rate from unemployment during the Great Recession period.

Participation Flows in the Data. The upper panel of Figure 1 plots separately the hazard rates from inactivity into employment (NE rate) and unemployment (NU rate), respectively, as well as their sum (i.e. the total inflow rate). Although individually the NE and NU inflow rates are themselves cyclical, during the Great Recession they moved in opposite directions such that the total inflow rate remained roughly constant. In other words, the propensity of inactive workers to enter the labour force remained constant, but new entrants became more likely to enter unemployment rather than find a job as vacancy postings and labour market tightness declined.

The lower panel plots the outflow rates of the employed and unemployed respectively (as well as their weighted sum, the total outflow rate). Overall the labour force outflow rate increased during the Great Recession, despite the fact that the outflow rate for the employed (the EN rate) declined slightly (from 2% to 1.8%) and that of the unemployed

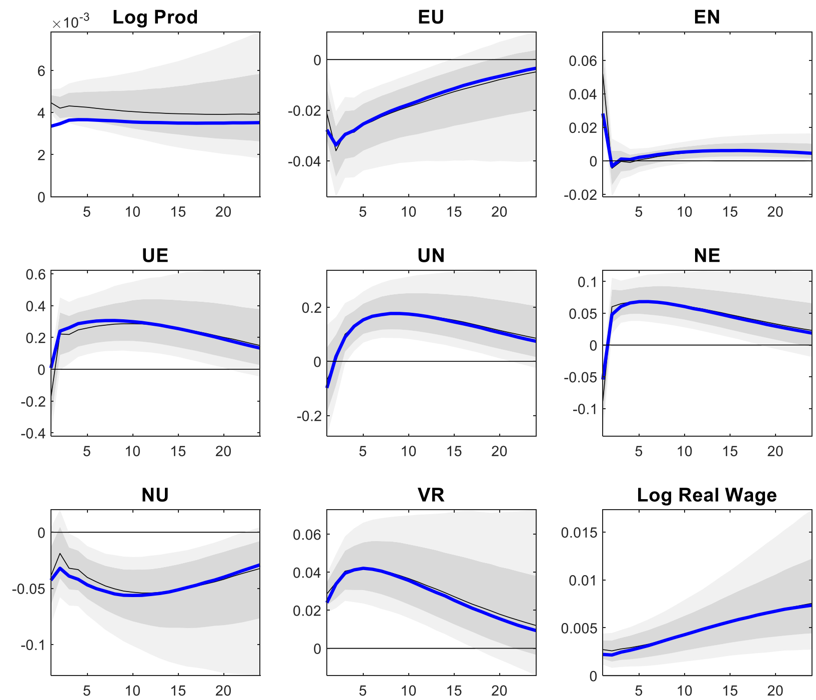
[9] Note that we exclude the Covid-19 period from our sample, on account of well-documented measurement issues of labour market flows in the LFS over this period stemming from declining response rates.

Figure 1. Participation flows in the United Kingdom, 2001Q4-2019Q4.



Notes: Upper panel plots the NE rate, NU rate, and the aggregate inflow rate (NU+NE). The lower panel plots the EN rate, UN rate, and the aggregate outflow rate ($(1-u)\text{EN} + u \cdot \text{UN}$). All series have been smoothed by taking centred four-quarter moving averages for visual clarity. Source: LFS.

Figure 2. IRFs for a productivity shock identified by sign- and magnitude-restrictions (blue lines), alongside Cholesky IRFs (black lines, and shaded CIs)



(the UN rate) fell substantially (from around 20% to 14%). This is due to the fact that during the Great Recession there was a large increase in the share of unemployed workers in the labour force, who on average have a labour force outflow rate which is an order of magnitude larger than employed workers. Overall the picture is comparable to that which Elsby et al. (2015) document for the United States.

More formally, we present evidence on the cyclicality of labour market flows conditional on an identified labour productivity shock, following the approach Cairo et al. (2022) who use data from the United States' equivalent of the UK LFS, the Current Population Survey (CPS).[10] We estimate a VAR containing the six labour market flow rates, vacancies and real wages, as well as labour productivity (ordered first). Given the fairly short sample length for the UK flows data compared to the US, we use Bayesian estimation following the approach outlined in Giannone et al. (2015). As in Cairo et al. (2022) we also run the estimation using two different identification schemes for robustness: (i) a

[10] In Appendix A we also provide unconditional evidence on the cyclicality of labour force flows based on the more standard approach of computing filtered second moments. The results are presented in Table A.1.

standard Cholesky approach, and (ii) a sign-restriction approach.[11] Figure 2 presents the estimated IRFs to a positive productivity shock under both identification schemes. In response to a positive labour productivity shock, separations into unemployment fall whilst job finding rates among the unemployed significantly increase as expected. Focusing on the behaviour of participation flows, the outflow rate from employment (EN rate) is insensitive to the shock whilst outflows from unemployment (UN rate) *increase*, and inflows into employment increase whilst inflows into unemployment fall, all consistent with the descriptive evidence presented above.

The Role of Outflows. To quantify the importance of participation flows for cyclical labour market dynamics we decompose variation of labour market stocks into their flow-based drivers over the sample period 2001Q4-2019Q4, following the now-standard approach used in Elsby et al. (2015, 2019) and in a UK context by Razzu and Singleton (2016) and Singleton (2018). Table 1 reports the contribution of each flow rate to the variance of employment, unemployment and the labour force participation rate (LFPR). Unsurprisingly, participation flows play a key role in driving variation in the aggregate labour force participation rate (LFPR, around 84%). However these flows also account for non-negligible fractions of the observed variation in the employment-to-population ratio (EPOP, 37%) and the unemployment rate (UR, 27%). The unemployment outflow (UN) rate plays an important role in accounting for unemployment dynamics, accounting for about 20% of variation in the unemployment rate alone.

Focusing more specifically on the Great Recession period, the upper panel of Figure 3 shows that in addition to the large contributions from the well-documented cyclical movements EU and UE rates, the procyclical decline in the UN rate played a key role in particular for explaining why unemployment in the UK remained *persistently* high in the years after the initial rise, as unemployed workers dropped out of the labour force at a slower rate than usual. Despite this decline in unemployment outflow rate, overall the LFPR exhibits a significant decline at the onset of the Great Recession because of the increase in the number of unemployed workers during the GFC, who are much more likely to leave the labour force than employed workers. Although the EU and UE rates only account for around 10% variation in LFPR over the whole sample (see Table 1), these flows play a much more significantly role in driving LFPR during business cycle episodes due

[11] For the sign-restriction approach the identifying assumptions are restrictions on the responses of the EU rate, the UE rate, the vacancy rate and productivity. The productivity response is restricted to be of a similar magnitude to the shock identified by the Cholesky decomposition; the UE and vacancy rate responses are restricted to be positive in response to this productivity shock; while the EU rate response is restricted to be negative.

Table 1. Variance decomposition of changes in labour market stocks

	EU	EN	UE	UN	NE	NU	initial value	residual
EPOP	0.27	0.12	0.38	-0.02	0.30	-0.06	0.01	0.01
UR	0.31	-0.01	0.40	0.21	0.04	0.03	0.00	0.02
LFPR	0.08	0.41	0.07	0.04	0.35	0.04	0.00	-0.01

Notes: This table reports the decomposition of labour market stocks according to contribution by each flow rate following the approach in Elsby et al. (2015). All data cover the sample period 2001Q4-2019Q4.

to their effect on changing the composition of the labour force.[12]

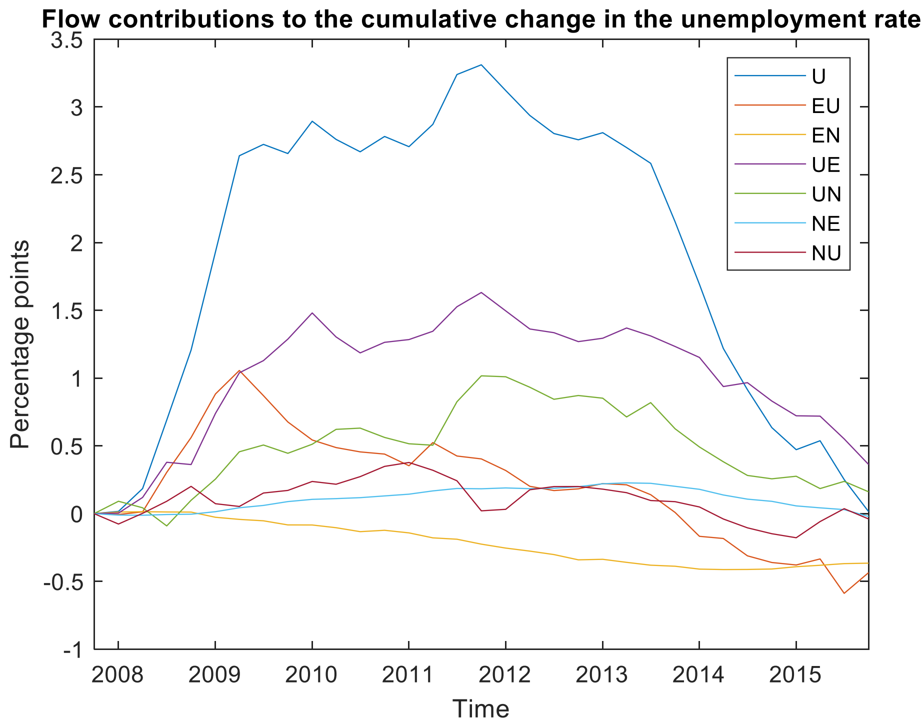
2.2 Labour Market Attachment, and the Importance of Previous Employment Status

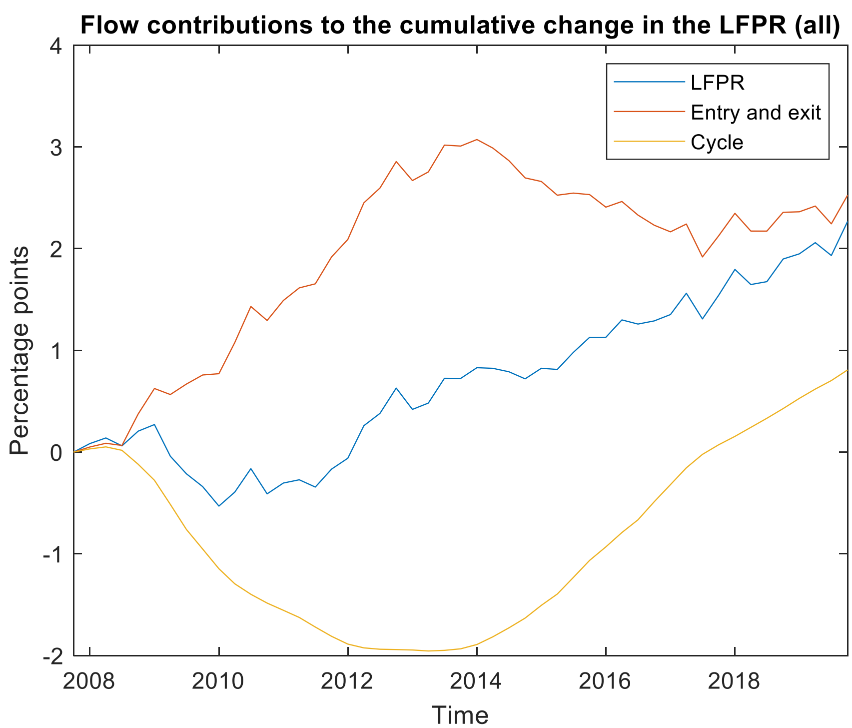
By labour market *attachment* we are referring to the propensity of an individual employed or unemployed worker to leave the labour force (i.e. the probability of an E-N or U-N transition). A higher degree of attachment reflects a lower propensity to leave the labour force. In this section we first present some descriptive evidence illustrating that there is heterogeneity in the degree of labour force attachment across a variety of worker characteristics, and that during the Great Recession the decline in the UN rate is correlated with the composition of unemployment shifting towards workers with characteristics associated with higher attachment. We then attempt to more formally quantify the relative importance of different characteristics in determining attachment, providing evidence that in the data whether a worker enters unemployment from employment or inactivity - i.e. their *previous labour force status* - is the most important determinant of an individual's labour market attachment when controlling for other worker characteristics we observe in the data.

Compositional Shifts Among the Unemployed. Again similarly to what Elsby et al. (2015) document for the United States, Table 2 outlines (i) the unemployment exit probabilities (UN and UE rates), (ii) the average shares of the unemployment pool in the periods 2005-7 and 2010-12, and (iii) the change in the shares, by worker characteristic subsample. Specifically, we focus on: gender, age, education, and previous activity before unemployment. The first column in Table 2 illustrates that different worker character-

[12] This mechanism is highlighted in Hobijn and Sahin (2021), who argue that these changes in the composition of the labour force across employment and unemployment states are responsible for driving the lower frequency *participation cycle*. During downturns countercyclical unemployment decreases the average degree of labour market attachment among the existing labour force. Even though unemployment outflows are procyclical and contribute to unemployment volatility, participation still declines because on average unemployed workers are much more likely to leave the labour force than those in employment.

Figure 3. Participation flows in the United Kingdom, 2001Q4-2019Q4.





Notes: The upper panel plots the path of the unemployment rate relative to its 2008Q1 value during the Great Recession period (blue line) as well as the contributions of each of the 6 labour market flow rates. The lower panel does the same for the LFPR (blue line), where we group flow rate contributions into those from the 'Cycle' (the EU and UE rates) and 'Entry and exit' (the NE, NU, EN, and UN rates, i.e. participation flows). Source: LFS and Singleton (2020).

istics are associated with higher labour market attachment in unemployment, notably being male, prime-age, holding a degree (or more), and whether a worker was previously working before being unemployed. In the final column we illustrate that there was a broad-based shift towards these worker groups with higher degrees of labour market attachment within the unemployment pool pre- and post-GFC, consistent with the declining unemployment outflow rate over this period. This evidence is suggestive of compositional effects in the pool of unemployment playing a key part in accounting for the procyclical outflow rate among the unemployment.[13]

Table 2. Unemployment hazard rates and compositional shifts by characteristic

Subgroup	Unemployment exit prob.			% 2005-2007	% 2010-2012	Δ%
	UN	UE	$UN+UE$			
Gender:						
male	0.14	0.26	0.40	56.51	57.08	**0.57**
female	0.23	0.27	0.50	43.49	42.92	-0.57
Age:						
16-24	0.19	0.29	0.48	40.5	37.77	-2.73
25-54	0.16	0.26	0.42	50.55	52.92	**2.37**
55+	0.24	0.19	0.43	8.94	9.3	0.36
Education:						
no degree	0.19	0.24	0.43	88.59	85.12	-3.47
degree	0.14	0.38	0.52	11.41	14.88	**3.47**
Previous activity:						
working	**0.11**	0.30	0.41	44.84	47.1	**2.26**
ft ed or training or on scheme	0.22	0.26	0.49	25.28	26.32	1.04
looking after family or home	0.28	0.18	0.46	17.06	16	-1.06
doing something else	0.20	0.22	0.42	12.81	10.57	-2.24

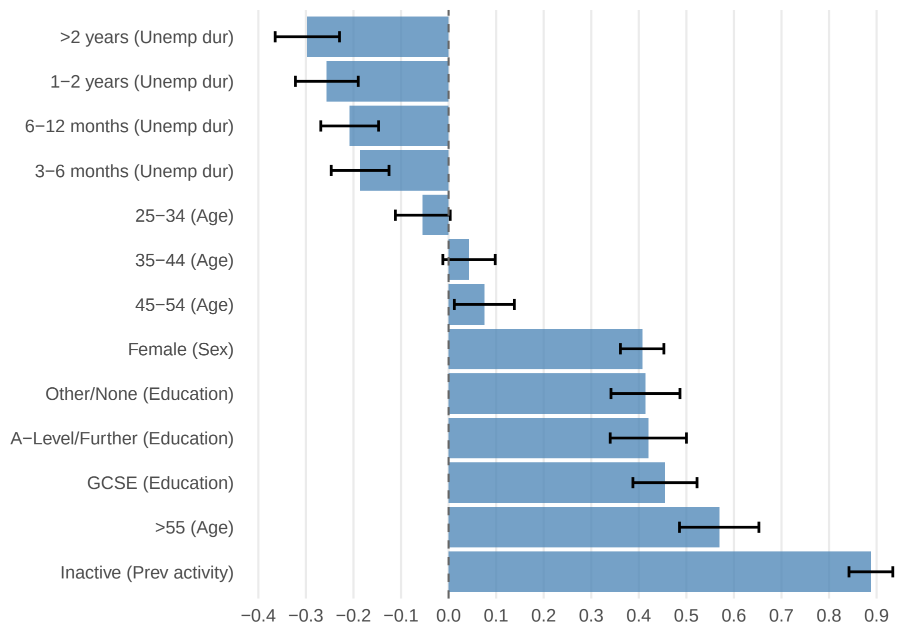
What Determines Labour Market Attachment of the Unemployed? To more formally quantify the relative importance of different worker characteristics for labour force attachment among the unemployed (i.e. the UN hazard rate), we estimate a cross-sectional logit model for U-to-N transitions in our sample conditional on worker characteristics. More explicitly, we estimate the following specification:

$$\log\left(\frac{P(UN_i=1|X_i)}{P(UN_i=0|X_i)}\right)=\alpha_i+\mathbf{X}_i'\beta_i+\varepsilon_i \tag{1}$$

where UN_i is an indicator taking a value of 1 if an unemployed worker transitions out of the labour force and 0 otherwise, and $\mathbf{X}_i$ is a vector of worker characteristics, namely:

[13]Figure **??** in Appendix C presents a counterfactual path of the aggregate UN rate over the Great Recession period using a shift-share approach, i.e. we generate the UN rate that we would have observed holding the composition of the unemployment pool fixed over this period. This analysis reveals that compositional changes by previous status and unemployment duration play a significant role in accounting for the procyclicality in the aggregate UN rate.

Figure 4. Multinomial logit coefficients for labour force attachment



Notes: The blue bars in the figure plot the estimated coefficients from the logistic multinomial regression of UN_i on worker characteristics, capturing the log-odds for each characteristics conditional on other covariates. The standard errors are computed at the 95% level. Source: LFS.

age, gender, educational attainment, unemployment duration, and previous employment status.[14]

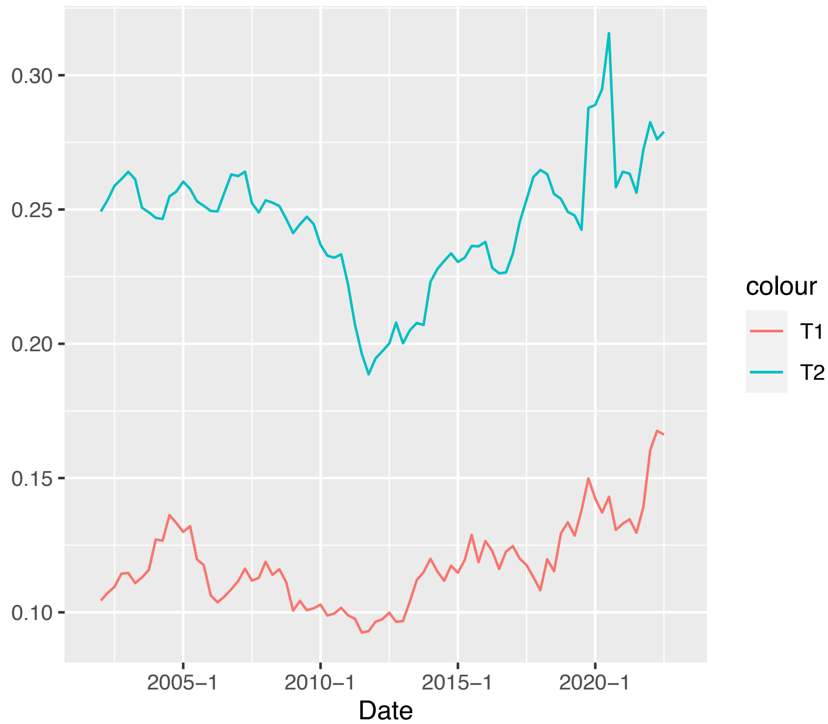
Coefficient estimates from the logit estimation are plotted in Figure 4.[15] Broadly speaking, lower attachment (higher UN_i) is associated with being older, female, having lower educational attainment, shorter unemployment duration, and entering unemployment from inactivity (rather than employment). Overall, out of all the individual characteristics we can control for our results suggest that a worker's previous labour force status before unemployment (i.e. their unemployment 'type') is the strongest predictor as to whether or not an unemployed worker exits the labour force. The estimated log-odds coefficient of 0.888 implies that, controlling for other worker characteristics, unemployed workers who were previously inactive are around 2.5 times more likely to leave the labour force than those who were previously employed.

Finally, in Figure 5 we plot the time series of the UN rate by previous employment status, where 'Type 1' refers to unemployed workers who were previously employed and 'Type

[14]We also include quarterly fixed effects in our baseline specification.

[15]The full estimation results for each logit specification are reported in Table A.2, where we incrementally control for the full set of worker characteristics in our dataset.

Figure 5. UN rate by previous employment status



Notes: The figure plots the UN rate of previously employed workers ('T1', red line) versus that of previously inactive workers ('T2, blue line). Source: LFS.

2' refers to those who were previously inactive.[16] In addition to the significant difference in the level of the UN rate over the sample, reflecting greater attachment of previously employed workers, it can also be seen that the UN rates by unemployment type exhibit different cyclical properties. Notably, the UN rate of previously inactive workers displays strong procyclicality during the GFC period, whereas that of previously employed is comparatively acyclical. Therefore, in addition to a greater share of Type 1 unemployed workers in the unemployment pool with greater attachment due to the heightened number of job separations, previously inactive workers also became more attached over this period, both of which contribute to the overall decline in the aggregate UN rate we observe during the Great Recession.[17]

[16]Note that we retain this classification of Type 1 and Type 2 unemployment for the remainder of the paper.

[17]Further analysis here suggests that a large amount of the increase in attachment among Type 2 unemployed workers post-2010 is driven by social security recipients and is related to changes in social welfare policy around this time. Figure C.2 plots UN rate for all Type 2 workers ('T2') against that for the subsample of Type 2 workers receive benefits ('T2b'), for which the decline in the UN rate is significantly more pronounced. We wish to thank Doug Rendle for this insight.

3 Search Effort and Previous Labour Force Status

Our main measure of labour force attachment, the individual propensity of an unemployed worker leaving the labour force UN_i, is only observed quarterly in our sample and is therefore subject to well-known issues of time aggregation. For instance, between any two quarters UN_i is determined by (at least) two forces: (i) the probability an unemployed worker is *unsuccessful* in their job search, which depends on their individual search effort e as well as aggregate contact rate $p(\theta)$ (which is a function of labour market tightness θ), and (ii) conditional on being unsuccessful, the likelihood of that worker choosing to reduce their search effort to the extent that they are subsequently classed as being economically inactive in the next quarter, i.e. their search effort drops below some threshold $\underline{e}$:

$$UN_i = \underbrace{(1 - e_i p(\theta))}_{\text{Unsuccessful in job search}} \times \underbrace{\Pr(e_i' < \underline{e} | e_i)}_{\text{Reduce search effort below 'active' threshold}}$$

A higher level of individual search effort e_i will be associated with a higher individual job finding rate and therefore a lower UN_i. In this section we examine the extent to which differences in search effort based on previous labour force status may be driving the differences in the level and cyclicality of UN rates by previous labour force status we have documented in the data.

3.1 Estimating Search Intensity

One key challenge is that we do not directly observe search effort in the UK LFS. However, by taking a standard view on the matching process we can utilise information on individual labour force transitions in the LFS to estimate an implied distribution of individual search effort, following the approach in Barnichon and Figura (2015) and previously applied to the UK LFS in Pizinelli and Speigner (2017). More specifically, we can exploit the fact that under the assumption of random matching an individual job finding rate can be expressed as:

$$p_{i,t} = \frac{e_{i,t}}{e_t} \frac{m_t}{u_t + n_t}$$

where $e_{i,t}$ and e_t are individual and aggregate search intensity respectively, m_t is the number of matches, and $\{u_t, n_t\}$ are the stocks of unemployed and inactive workers who are all assumed to search for jobs but with differing degrees of effort. We assume that individual search intensity e_i is an exponential function of observable characteristics:

$$e_i = \exp(\mathbf{X}_i'\beta)$$

where $\mathbf{X}_i$ is a vector of worker characteristics. Job finding rates can be converted into discrete time-adjusted rates according to: $P_{i,t} = 1 - \exp\left(-\frac{e_{i,t}}{e_t} p_{i,t}\right)$. We can then estimate the vector β via maximum likelihood and construct an estimated individual (relative) search intensity.[18] See Appendix A for further details.

3.2 Search Effort in the Cross-Section

Figure 6 plots the estimated distributions of (relative) search effort by labour force status. Firstly, comparing the distributions of unemployed and inactive workers (upper panel) shows that, as we would expect, on average workers classed as inactive have a substantially lower search intensity relative to the average searcher, where there is a large mass of inactive workers whose search effort is very low (close to zero). In contrast the distribution among the unemployed displays greater variance but with significant mass above 1 (the average), reflecting the fact that unemployed workers are conventionally defined as full-time job seekers.

The lower panel of Figure 6 instead compares the search intensity distributions of the unemployed based on previous labour force status (where 'Type 1' refers to those previously in employment, and 'Type 2' to those previously inactive). Perhaps surprisingly, the difference between the search intensity distributions of the unemployed based on previous labour force status is relatively small.[19] Given the approach we adopt for estimating search intensities, this suggests that the job finding rate for an unemployed worker is not strongly affected by their previous labour force status, controlling for other worker characteristics.[20] Overall this evidence suggests that observed differences in UN rates based

[18]Note that this approach only identifies the *relative* search intensity of an individual, as this is ultimately what matters for individual job finding transitions via the matching function. Variation in job finding outcomes which cannot be explained by differences in worker characteristics under this approach will be absorbed by differences in (relative) search effort.

[19]There is a small but significantly significant difference in the mean relative search effort across the two subsamples: 1.84 for Type 1 compared to 1.91 for Type 2. A two-sided Kolmogorov-Smirnov test indicates that whilst we can reject that the estimated distributions of search effort for Type 1 and Type 2 unemployed are from the same underlying distribution, a test statistic of 0.052 indicates that there is at most a 5.2 percentage point difference in the cumulative densities, which indicative of a relatively small difference between the two distributions.

[20]In Appendix A we provide evidence on the effect of unemployment 'type' on individual job finding rates controlling for other worker characteristics by estimating a cross-sectional logit model similar to the specification in equation 1. The results can be found in Table A.3.

on previous employment status are not driven by differences in the level of search effort.

3.3 Search Effort Over the Business Cycle

Although on average the search effort of Type 1 and Type 2 unemployed workers looks broadly similar in the cross-section, over time the search effort of these different groups may behave differently in such a way that drives the apparent difference in the cyclicality of the respective UN rates plotted in Figure 5. For instance, if the search effort of Type 2 unemployed workers is strongly procyclical relative to Type 1 unemployed this may account for the procyclicality in the Type 2 UN rate.

Unconditional evidence. In Figure 7 we plot the implied time series for within-group search intensity over the sample period. For the inactive workers we find that within-group search intensity is essentially constant throughout the sample. For unemployed workers we find some evidence that search intensity declined during the Great Recession before recovering by 2015.[21] However we do not find evidence of significant cyclical differences in the search intensity of Type 1 and Type 2 workers.

To remove the influence of any trends over the sample period we also present standard unconditional cyclical properties of within-group search intensities in Table 3. The cyclical component of search intensity among the unemployed is slightly more volatile than for the inactive, as well as more persistent. This appears to be driven by the search effort of Type 1 unemployed workers, whose search effort is more volatile (0.03) and marginally more persistent (0.908) than that of Type 2 (0.023 and 0.904 respectively) over the business cycle. Nevertheless, cyclical movements in search intensity among the unemployed appear to be uncorrelated with the state of the economy, which again suggests that differences in search effort are not driving cyclical movements in UN rates.

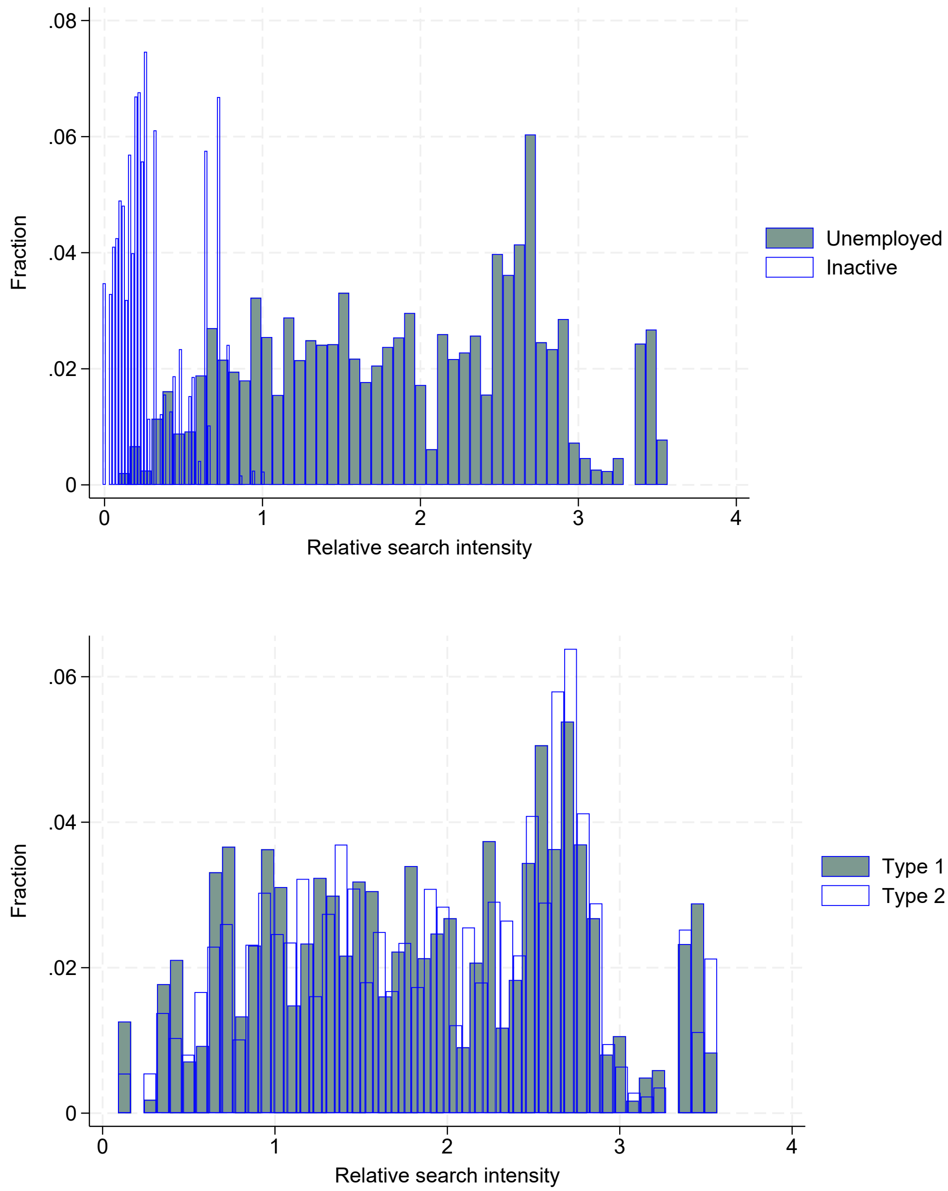
Conditional evidence. Finally, using a simple SVAR model we study the cyclical properties of the different within-group search intensities conditional on aggregate shocks (namely, an identified shock to labour productivity). Specifically, we estimate the following VAR specification:

$$\mathbf{y_t} = \mathbf{c} + \mathbf{A}(\mathbf{L})\mathbf{y_{t-1}} + \mathbf{v_t} \tag{2}$$

where $\mathbf{c}$ is a constant term, $\mathbf{A}(\mathbf{L})$ is a lag polynomial, and $\mathbf{v}_t \sim (0, \mathbf{\Omega})$ is a vector of error terms with mean zero and variance-covariance matrix $\mathbf{\Omega}$. We focus on the following

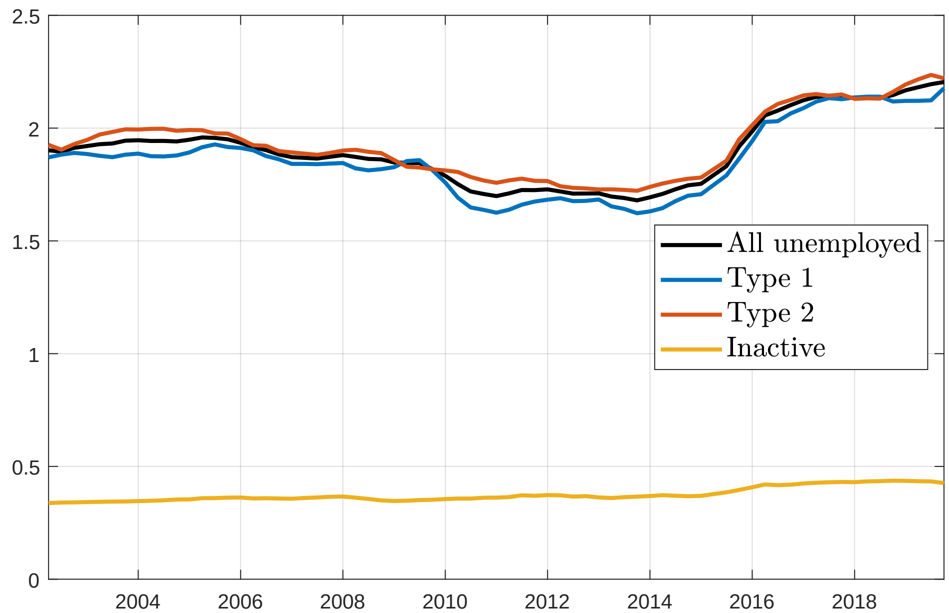
[21] Interestingly this differs somewhat with the findings for the US documented in Mukoyama et al. (2018) using more direct evidence on search effort from the American Time Use Survey (ATUS) and the Current Population Survey (CPS), who find that the intensive margin of search effort is strongly countercyclical.

Figure 6. Comparing relative search intensities between searchers



Notes: The upper panel plots the distributions of (relative) search intensities for the unemployed vs. the inactive estimated as described in the text. The lower panel instead compares the distributions for unemployed workers based on their previous labour force status, where 'Type 1' refers to unemployed workers who entered unemployment from employment, and 'Type 2' unemployed who entered from inactivity. Source: LFS.

Figure 7. Search intensity within-group over the business cycle



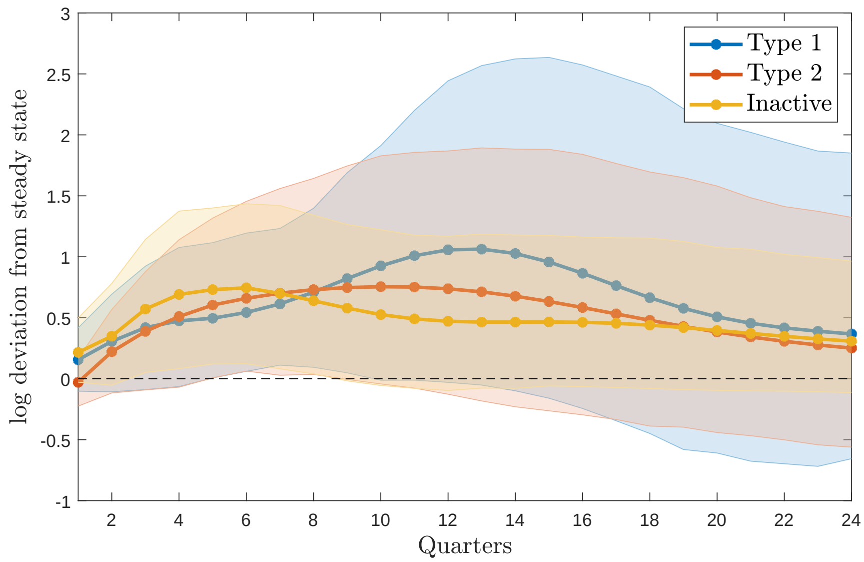
Notes: The figure plots the constructed time series of (relative) search intensities for (i) all unemployed workers (black line), (ii) Type 1 unemployed (blue line), (iii) Type 2 unemployed (red line), and (iv) the inactive (yellow line). All series have been smoothed by taking centered four-quarter moving averages for visual clarity. Source: LFS.

Table 3. Cyclical Properties of Within-Group Search Intensity

x	$s_{u,t}$	$s_{u1,t}$	$s_{u2,t}$	$s_{I,t}$
σ_x	0.025083	0.030212	0.023712	0.019491
$\mathrm{corr}(x, x_{-1})$	0.92144	0.90806	0.90416	0.8314
$\mathrm{corr}(x, y)$	-0.014963	-0.052584	0.031166	0.41968

Notes: This table reports the standard deviation, autocorrelation and correlation with (real) GDP for the time series average within-group search intensity for the unemployed, Type 1 unemployed, Type 2 unemployed, and the inactive. All series are logged and HP filtered using $\lambda = 1600$.

Figure 8. Impulse Responses of Search Intensity to a Productivity Shock



Notes: The figure plots the empirical response of search intensity to a productivity shock for: (i) Type 1 unemployed (blue line), (ii) Type 2 unemployed (red line), and (iii) Inactive (yellow line). Solid lines denote the mean response and shaded region denotes 95% confidence interval computed via bootstrapping. Source: LFS & ONS.

vector of endogenous variables:

$$\mathbf{y_t} = \left[\ln ALP_t, \ln s_{x,t}, \ln \theta_t\right]$$

where ALP is average labour productivity, s_x is our constructed time series of within-group average search intensity indexed by $x = \{u_1, u_2, n\}$, and θ is labour market tightness (defined as the ratio of vacancies to unemployed). To identify a shock to labour productivity we impose a standard recursive identification scheme (i.e. a Choleski decomposition of $\mathbf{\Omega}$) where we order labour productivity first, followed by within-group search effort and tightness.[22] Figure 8 plots the empirical IRFs of within-group search effort of Type 1 unemployed, Type 2 unemployed and the inactive to a one standard deviation positive innovation in labour productivity. The empirical response of search intensity across all groups is small ($< 1\%$) and only marginally statistically significant. Again this evidence further suggests the absence of any differences in the cyclical behaviour of within-group search effort.

[22]This identification strategy imposes that shocks to productivity can affect search intensity and tightness contemporaneously, whilst shocks to search intensity can only have a contemporaneous effect on tightness and tightness shocks only affect other variables with a lag.

3.4 Summary

Overall this evidence suggests that differences in observed UN rates by previous labour force status, both the level and their dynamics, are not driven by differences search effort behaviour but are instead genuinely driven by differences in the degree of labour market attachment, i.e. the propensity of these workers to maintain a sufficiently high search effort for the duration of a non-employment spell. In the next section we outline a simple reduced form mechanism capturing differences in labour force attachment based on previous employment status, which we embed into an otherwise standard search & matching framework and study its implications.

4 Implications of Heterogeneous Attachment in Matching Models

The empirical evidence presented in the previous sections has shown that procyclicality in labour force outflows from unemployment are correlated with compositional shifts among the unemployment pool, that previous labour force status is the strongest predictor of labour market attachment, and that this finding is not driven by differences in the level or cyclicality of search effort. In this section we extend a basic search & matching model to allow for heterogeneous labour market attachment among the unemployed which is consistent with our empirical findings. We then use the model to isolate the role that this key composition effect plays in explaining labour market dynamics, both over the whole sample and specifically during the Great Recession. We then compare our findings to those in Mukoyama et al. (2018) who study the role of cyclicality in the *intensive* margin of worker search effort over the business cycle, whereas in comparison we study the implications of compositional changes among searchers with heterogeneous labour market attachment.[23] Given the rest of the model is well-known we leave full details to Appendix B.

4.1 Environment

Workers. At any point in time workers are either in employment or out of employment. In a manner consistent with the estimated distributions of search effort presented in Section 3 we assume that all workers out of employment are characterised by an idiosyncratic value of search effort $e \in [0, \infty)$, which for simplicity we initially assume

[23] In contrast to Mukoyama et al. (2018) We assume that search effort follows an exogenous process where there is no cyclicality in search intensity at the individual level, instead fluctuations in aggregate search intensity are driven only by changes in the composition of non-employed workers, where the stochastic process governing search effort is different based on labour force status.

is exogenous and follows a stochastic process outlined below.[24] There exists an exogenous, time-invariant threshold for search intensity $\underline{e}$ below which a worker is classified as inactive (n), otherwise a worker is classed as unemployed (u). In this environment all non-employed workers search but with different intensities and the labour force status of the non-employed is determined by their search intensity relative to this threshold. This threshold being time-invariant is consistent with the earlier evidence that the search effort of inactive workers being constant over time (see Figure 7). Workers in employment earn a wage $w(a)$ which depends on an idiosyncratic value of job-specific productivity a (described below). Non-employed workers earn a flow value $b(e)$ capturing leisure or other benefits associated with non-employment, and in general will depend negatively on search effort (i.e. $b'(e) \leq 0$).

Search intensity. The search intensity of non-employed workers e is exogenous and drawn from a distribution $F(e)$. In order to capture the different degrees of labour market attachment conditional on previous labour force status that we have documented in the data, we assume that workers re-draw from $F(e)$ at different frequencies depending on: (i) their current search intensity e (i.e. their labour force status), and crucially (ii) how they entered non-employment (i.e. their previous activity). A greater redraw frequency implies a lower degree of labour market attachment (which we illustrate further below). Workers who enter unemployment directly from employment due to separation ('Type 1' unemployed) re-draw with probability $\lambda_{u_1} \in (0, 1)$, whilst we assume that 'Type 2' unemployed re-draw e in every period conditional on not finding a job or drawing $e < \underline{e}$ and transitioning to inactivity (i.e. we normalize $\lambda_{u_2} = 1$). In this manner, consistent with the evidence described in Section 3, the persistence of individual search effort (i.e. labour market attachment) is independent of the level of search effort and is greater for unemployed workers who enter from job separations ('Type 1'). Finally, we assume inactive workers (i.e. $e < \underline{e}$) re-draw search intensity with probability λ_n each period, where those who draw search intensity $e \geq \underline{e}$ become Type 2 unemployed.[25]

Vacancies, wages & separations. New jobs are created by firms who can freely enter the market by posting vacancies v_t at period flow cost $\kappa > 0$. Existing jobs produce match output $Z_t a$, where a is a job-specific productivity level which is redrawn at the beginning

[24] In practice we could extend the model to allow for an endogenous search intensity decision along the lines of Shimer (2004) or Mukoyama et al. (2018). To generate the heterogeneity in the choice of e that we need, we would need to assume some source of heterogeneity in this optimal choice, for example heterogeneous search disutility costs, such as in Christiano, Trabandt and Walentin (2022).

[25] Whilst the assumption that the redraw frequency for inactive workers λ_n is distinct from unemployed workers is not key for our story, allowing inactive workers to redraw at a different frequency allows the model to match all 6 labour market flow rates exactly in steady state.

of every period from a distribution $G(a)$ and the log of Z_t evolves according to an AR(1) process. Wages are determined via Nash bargaining such that workers always receive a fixed fraction $\eta \in (0,1)$ of the joint match surplus. As standard this implies the existence of a threshold value $\underline{a}$ below which both workers and firms will agree to terminate the match. Worker-firm pairs can also separate exogenously for reasons unrelated to productivity with probability $\delta^x \in (0,1)$. We assume that workers who separate endogenously due to job-specific productivity shocks have higher initial search effort and are classed as unemployed (i.e. draw a search intensity $e \geq \underline{e}$), and also have greater labour market attachment (i.e. are Type 1 unemployed with redraw probability λ_{u_1}). In contrast workers who separate exogenously are assumed to have lower initial search effort and flow directly into inactivity (i.e. $e < \underline{e}$).[26]

Matching. A non-employed worker with search effort e finds a job with probability $p(e, \tilde{e}, \theta)$, where $\tilde{e}$ is aggregate search effort, θ is labour market tightness (i.e. the ratio of vacancies to searchers). This is assumed to derive from a matching function $M(\tilde{e} \cdot \tilde{s}, v) = \int p(e, \tilde{e}, \theta) dF(e) \cdot \tilde{s}$, where $\tilde{s}$ is the number of searchers. Among the unemployed, the average job finding rate can be expressed as $p_u(\tilde{e}, \theta) = \int_{\underline{e}} p(e, \tilde{e}, \theta) \frac{dF(e)}{1-F(\underline{e})}$, whilst for the inactive the average job finding rate is: $p_n(\tilde{e}, \theta) = \int^{\underline{e}} p(e, \tilde{e}, \theta) \frac{dF(e)}{F(\underline{e})}$. Similarly, a vacant job meets with a worker with probability $q(\tilde{e}, \theta)$. Note that whilst average search intensity $\tilde{e}_t$ will fluctuate over the business cycle due to fluctuations in the pool of searchers (the extensive margin), the average *within-group* search intensity (i.e. the intensive margin) remains constant because the exogenous threshold $\underline{e}$ and the distribution $F(e)$ are assumed to be time-invariant.[27]

Key Mechanism. The simple but novel mechanism we introduce into this otherwise standard DMP framework ensures that unemployed workers have comparable degrees of search effort conditional on previous status, but differing degrees of labour market attachment consistent with empirical evidence. Under the assumptions outlined above,

[26] These assumptions about the properties of search effort and attachment conditional on the type of job separation that occurs allows the model to be consistent with the empirical evidence on labour force outflows in two ways: (i) it ensures the EN flow rate in the model is acyclical by construction, and (ii) that the composition of unemployment during recessions shifts towards workers who were previously employed and have higher labour market attachment.

[27] We later exploit this fact when calibrating the model together with a functional form for the matching function which ensures that the overall labour force inflow rate is constant over the business cycle, consistent with the evidence presented in Section 2.

the UN rate of a Type j unemployed worker can be expressed as:

$$UN_{t,j} = \underbrace{(1-p_u(\tilde{e}_t,\theta_t))}_{\text{Unsuccessful in job search}} \cdot \underbrace{\lambda_j F(\underline{e})}_{\text{Reduce search intensity below } \underline{e}}, \quad j \in \{1,2\}$$

and average unemployment duration condition on previous labour force status can be expressed as:

$$D_{u_j} = \frac{1}{\underbrace{p_u(\tilde{e}_t,\theta_t)}_{\text{UE rate}} + \underbrace{(1-p_u(\tilde{e}_t,\theta_t))\cdot\lambda_j F(\underline{e})}_{\text{UN rate}}}$$

As job finding rates of Type 1 and Type 2 unemployed workers are assumed to be identical, again consistent with evidence from search effort outlined in Section 3, the difference in labour force attachment between Type 1 and Type 2 unemployed workers is determined by the difference in their search intensity persistence, $\lambda_{u_2} - \lambda_{u_1}$. A lower degree of attachment among Type 2 workers implies a relatively lower level of search effort persistence, i.e. $\lambda_{u_2} > \lambda_{u_1}$. Furthermore, during downturns the increase in the aggregate separation rate δ_t leads to a rise in the share of Type 1 unemployed workers in the unemployment pool as in the data (see final column in Table 2), which reduces the aggregate UN rate and increases labour market attachment among the unemployed purely via a composition effect.

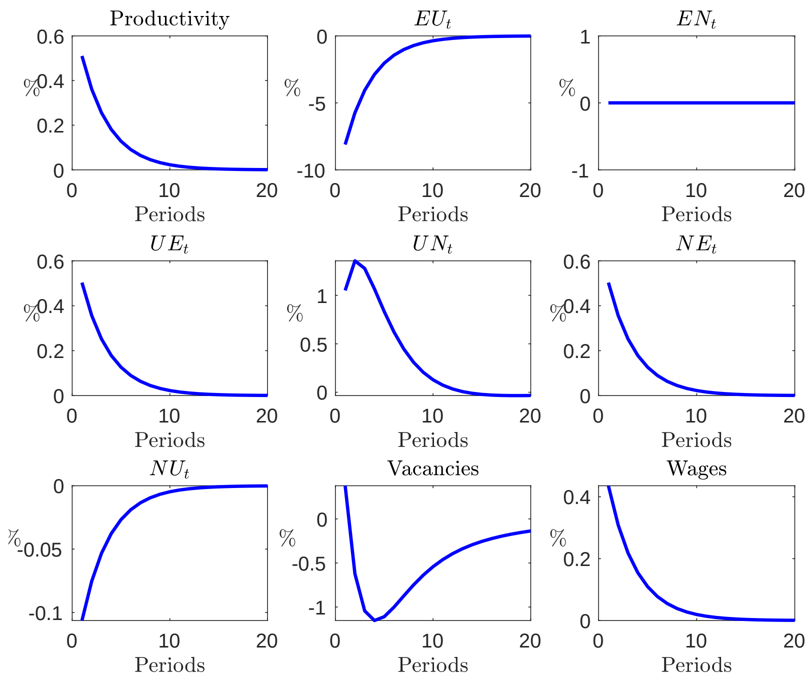
Table 4. Steady state performance: Model vs. Data

Empirical concept	Model concept	Data	Model
UR	$\frac{u}{1-n}$	0.059	0.041
LFPR	$1-n$	0.774	0.805
EU rate	$(1-\delta^x)G(\underline{a})$	0.012	0.012
EN rate	δ^x	0.019	0.019
UE rate	$p_u(\tilde{e},\theta)(1-\delta)$	0.268	0.268
UN rate	$(1-p_u(\tilde{e},\theta))F(\underline{e})\frac{\lambda_{u_1}\tilde{u}_1+u_2}{\tilde{u}} + p_u(\tilde{e},\theta)\delta^x$	0.057	0.057
NE rate	$p_n(\tilde{e},\theta)(1-\delta)$	0.182	0.182
NU rate	$p_n(\tilde{e},\theta)(1-\delta^x)G(\underline{a}) + (1-p_n(\tilde{e},\theta))\lambda_n(1-F(\underline{e}))$	0.047	0.047

4.2 Cyclical properties

IRFs. Figure 9 reports the model-generated IRFs for the same variables for which we estimated empirical IRFs in Figure 2 conditional on a comparable aggregate labour productivity shock. The overall takeaway is that our simple DMP model with heterogeneous attachment and search effort-based definitions of labour force status is able to qualita-

Figure 9. IRFs for a productivity shock in the calibrated model. Expressed as log deviations from steady state levels.



tively capture the joint behaviour of all 6 labour market transition rates in a manner consistent with what we document in the data, albeit with quantitative deficiencies owing to the simplicity of the model.[28]

We first discuss how the model qualitatively matches the behaviour of the labour market transition rates. For reference, Table 4 reports the definitions of flow rates in the model as well as the empirical values we target in our parameterization. Firstly, considering separations out of employment, countercyclicality in the EU rate is driven by the standard job destruction threshold $\bar{a}_t$ which declines in response to an increase in Z_t, whilst the EN rate is constant by assumption. Next, we consider inflows into employment. The procyclicality in these rates is driven by two channels: (i) an increase in the matching probabilities $p_u(\tilde{e}, \theta)$ and $p_n(\tilde{e}, \theta)$, and (ii) a fall in job destruction (which in the model is capturing a time aggregation effect, i.e. workers have to first find jobs, and then survive separation). Moreover, these flows are proportional to each other given our assumptions regarding the matching function. Finally, we consider the flows between unemployment and inactivity. Although unemployed workers find jobs faster (which puts countercyclical pressure on

[28]Unlike the frameworks outlined in Krusell et al. (2017) or Cairo et al. (2022), our model does not require the presence of several additional, richer features to achieve this result.

UN flow in the model), the distribution of the unemployment pool shifts *away* from Type 1 unemployed workers (who have higher search effort persistence) due to the decline in job destruction. Overall this latter effect dominates and the UN flow is procyclical (as in the data).[29] The countercyclical NU flow is the outcome of a reduction in the number of inactive workers entering unemployment either directly or via employment. As worker contact rates increase, workers are more likely to find a job and enter employment (and less likely to transition into unemployment). This is amplified by the falling job destruction margin $\bar{a}_t$, which reduces further the number of inactive entering unemployment via employment.

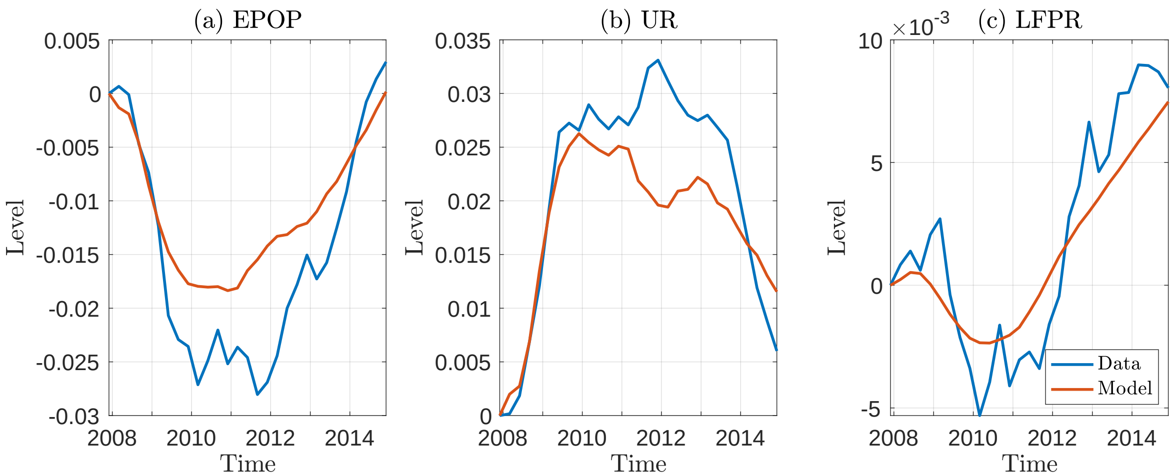
The remaining panels in Figure 9 display the corresponding responses of vacancies and wages, whilst the responses for labour market stocks are displayed in Figure C.3.[30] Labour force participation increases and unemployment falls in response to the shock, and the unemployment pool shifts towards Type 2 unemployed workers ($u_{1,t}$ declines by significantly more than $u_{2,t}$ due to the decline in job destruction). Aggregate search effort $\tilde{e}_t$ declines both because (i) the aggregate number of searchers declines, and (ii) the pool of searchers shifts away from workers who have greater attachment (higher search intensity). This latter effect is entirely driven by changes in composition, given that within-group search intensity is constant (as there is no intensive margin of adjustment for search effort in the model).

Business cycle moments. Tables C.2 report the cyclical properties of labour market flows and stocks from model simulations and compares them to the data. The results are broadly consistent with results from the model IRFs. Overall under our baseline calibration the model is able to match qualitatively the same co-movements of flows and stocks that we see in the data, although quantitatively the fit of the model can be significantly improved and still suffers from an inability to generate sufficient volatility relative to the data. Adopting standard approaches for generating additional volatility in matching models from the literature, namely: (i) a small-surplus calibration as in Hagedorn and Manovskii (2008), and (ii) allowing for wage rigidity, again helps generate substantially more volatility on the separation margin, job finding margin and participation margin,

[29] There is also a time aggregation channel operating on the UN flow which contributes to procyclicality: unemployed workers find new jobs faster, and are then subject to a 'retirement' shock δ_x in the next period before commencing production.

[30] The largest discrepancy between the model and the data is in the response of vacancies. Whilst initially job creation responds positively to the increase in aggregate productivity, after several periods job creation then declines persistently, driven by the strong and persistent decline in aggregate search effort which reduces the firm's contact rate $q(\theta)$. In contrast, empirical evidence in Figure 2 illustrates in the data that job creation increases strongly and persistently.

Figure 10. Labour market stocks in the Great Recession: Data vs Model. All series are normalized to zero at 2001Q1.



whilst making overall co-movement of flows with output more significant, and leading to realistic volatility in the stocks.[31].

Great Recession. Finally, we examine the fit of the model over the Great Recession period in Figure 10.[32] Overall the model is able to account for a large fraction of the fall in employment (1.6 p.p. compared to 2.7 p.p.), and essentially all of the initial 2.5 p.p. increase in unemployment. Looking at the model-implied flows relative to the data (see Figure C.4) reveals that whilst the model is able to reasonably capture dynamics in the EU rate (targeted) and UN rate (untargeted) over this period, the shortfall in volatility can be accounted for by the fact that the model generates less than half of the observed decline in the UE rate.

4.3 Heterogeneous Attachment and Unemployment Volatility

In our framework fluctuations in labour force participation reflect changes in the composition of search effort in the non-employment pool in a manner consistent with observed cyclicality of labour force flows. In this section we isolate the role of the particular composition effect we focus on in this paper - the previous activity of unemployed workers -

[31]More details about these alternative calibration strategies can be found in Appendix B. The results are reported in the bottom two panels of Table C.2

[32]This is an instructive exercise given that in the context of the UK labour market flows data we use in this paper the Great Recession is the only business cycle event in our sample. We solve for the appropriate sequence of shocks to aggregate labour productivity ϵ_t that allow us to exactly match de-trended labour productivity in the data over this period. We then feed this series through our baseline model and compare the implied behaviour of labour market stocks with the data.

for unemployment volatility. To do this we compare business cycle volatility in the baseline version of our model to a version where we shut down heterogeneity in search effort and attachment such that all non-employed workers search with the same intensity (i.e. $\sigma_F = 0$) and we normalize $e = 1$ for all non-employed workers.[33] Table 5 reports the results from this quantitative exercise, as well as corresponding moments in the data for reference.

Table 5. Unemployment volatility and participation

	$\text{std}(u) \times 100$	$\text{std}(EU) \times 100$	$\text{std}(UE) \times 100$
I. Data	6.12	9.12	6.07
II. DMP model ($e = 1$)	2.14	10.93	1.35
III. Baseline model	3.21	9.15	0.57

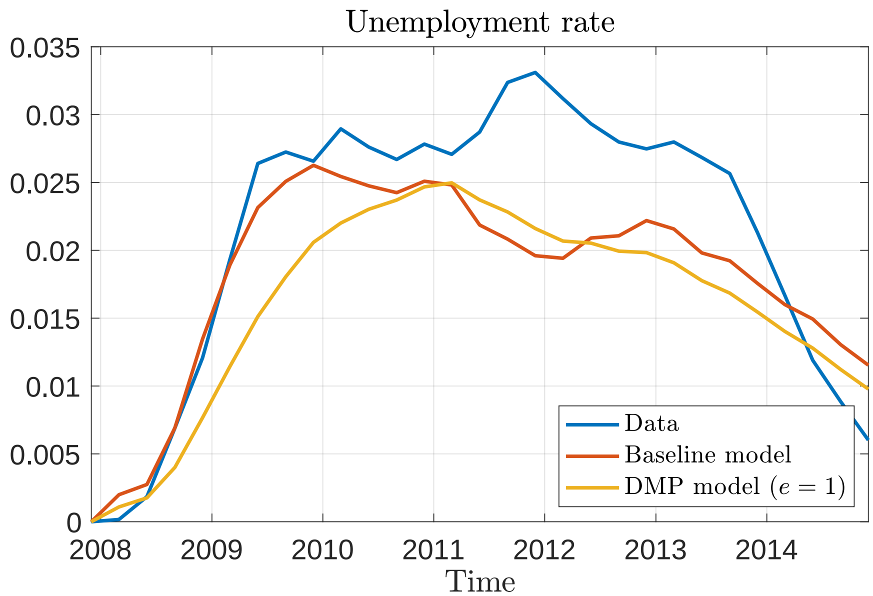
Notes: Simulated data are logged and HP filtered using smoothing parameter $\lambda = 1600$. Each replication computes simulated statistics from a sample of 120 quarterly observations. Reported statistics are averages over 100 replications.

Consider first the textbook DMP model with endogenous job destruction (i.e. $\sigma_F = 0$, $e = 1$). As expected, given the well-known issues with generating sufficient unemployment volatility under our calibration approach the model only generates around a 33% of the unemployment volatility we find in the data.[34] Results from our baseline model suggest that the presence of this composition effect actually *amplifies* unemployment volatility. In practice this is the outcome of two opposing forces: (i) changes in the composition of unemployed workers, and (ii) a GE effect on job creation by firms. Endogenous shifts in the composition of unemployment between Type 1 and Type 2 workers amplifies unemployment fluctuations via its effect on the aggregate UN rate, consistent with the role we highlighted in the data based on flow decompositions (see Table 1). During downturns higher endogenous job separations shifts the composition of the unemployment pool towards Type 1 who have higher persistence in their search effort compared to Type 2 workers. In general equilibrium, this dampens the fall in job creation, leading to a reduction in the volatility of the UE rate relative to the standard DMP model. Overall the effect on the UN rate dominates and in equilibrium we find that shifts in the composition of searchers amplify unemployment fluctuations.

[33] All workers are subsequently classed as unemployed as in the standard textbook model with endogenous job destruction, e.g. Pissarides (2000). For the purposes of the exercise we keep as many of the structural parameters of the model the same where possible. More details about this version of the model can be found in Appendix B.

[34] Fujita and Ramey (2012) show that the presence of endogenous job destruction already contributes somewhat to alleviating the severity of the unemployment volatility puzzle outlined in Shimer (2005).

Figure 11. Contribution of composition effect among searchers in the model over the Great Recession period. All series are normalized to zero at 2008Q1.



Further to this we can use the model to quantify the contribution of this composition effect for unemployment dynamics during the Great Recession. Figure 11 plots the unemployment outturn as well as the model-implied paths for unemployment during the Great Recession period generated from our baseline model and the version of the model where we shut down heterogeneity in search effort and attachment. We find that the decline in the UN rate present in our framework is important for better capturing the speed of the rise in unemployment at the onset of the Great Recession relative to the standard model, as well as amplifying the peak of the unemployment profile. Overall this suggests that the presence of both the endogenous job destruction margin alongside compositional effects on the participation margin relating to attachment amplify unemployment volatility.

Relationship to Mukoyama et al. (2018). Mukoyama et al. (2018) document empirically using US survey data that worker search effort is *countercyclical*, and then use a search & matching model with endogenous search effort to show that countercyclical search effort dampens labour market fluctuations. The findings we present above appear at first glance to contrast with those in Mukoyama et al. (2018), however in practice we view our analysis and results as complementary. Mukoyama et al. (2018) study the implications of fluctuations on the *intensive* margin of search effort (i.e. individual worker adjustments), and abstract from compositional effects reflecting heterogeneity in search effort across job searchers, i.e. in their framework e is endogenous but all workers make an identical choice of e. In contrast, our model essentially examines the opposite case - we abstract from movements on the intensive margin and focuses solely on the role of compositional effects within the pool of searchers, where we allow search effort to evolves differently across workers based on their previous labour market status in a manner consistent with differences in labour market attachment we document in the data.

5 Conclusion

In this paper we reexamine the role of participation flows in driving labour market dynamics. We documented that procyclical outflows among the unemployed appear to be driven by compositional shifts among the unemployed towards groups with higher labour market attachment, that previous labour force status is the most important determinant of labour market attachment among the unemployed when controlling for other observable worker characteristics, and that this does not appear to be driven by differences in search behaviour or job finding prospects. We then outlined a tractable extension to the textbook DMP model with endogenous separations whereby unemployed workers differ in their labour market attachment based on how they entered unemployment, in a manner consistent with the data. Our simple framework generates cyclicality in labour market flows across employment, unemployment and non-participation which are qualitatively consistent with empirical evidence. Our simple quantitative exercise suggests that the interaction between heterogeneous labour market attachment and job separations increases the volatility of unemployment by 50% relative to the baseline DMP model.

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A Empirical Appendix

A.1 Data

Sources. For labour force flows we use data from the two-quarter longitudinal UK Labour Force Survey (LFS). For each quarter, individual observations contain information on demographics, as well as labour force status for the current and previous quarter. The linked data allows us to construct measures of labour force flow rates for the UK. We apply the recommended survey weights in order to make the sample representative of the UK population. The full sample covers the period 1993Q1-2023Q4.

Constructing labour market flows. We construct labour market flows for those aged 16-64. In order to correct for inconsistencies between the flow and stock estimates, possibly due to non-random attrition or entry to and exit from the age-range, we adjust the transition rates following the approach taken by Elsby et al. (2015). This approach solves for the set of stock-consistent transition probabilities that minimizes the weighted sum of squares of the 'margin-error adjustments'.[35]

A.2 Additional evidence on the cyclical properties of labour market flows

Table A.1. Labour market flows: Cyclical properties

	EU	EN	UE	UN	NE	NU
std(x)	0.091	0.066	0.061	0.065	0.070	0.051
corr(x, Y)	-0.605	0.172	0.535	0.219	0.496	-0.256
corr(x, x_{-1})	0.359	-0.194	0.489	0.238	0.307	0.106

Notes: Data cover the sample period 2001Q4-2019Q4. All series are in logs and filtered using a HP filter using smoothing parameter $\lambda = 1600$ as standard for quarterly data.

Table A.1 presents unconditional cyclical properties of UK labour market flow rates individually based on standard filtering of the time series. For other examples of this see Elsby et al. (2015) and Krusell et al. (2017) for the US, and Smith (2011) using UK data from the British Household Panel Survey (BHPS).The magnitudes of the cyclical fluctuations across all the flow rates are fairly similar. As is well documented elsewhere, separations into unemployment are strongly countercyclical (corr. with output -0.6) whilst the job finding rate among unemployed is strongly procyclical. We find that inflows into employment from inactivity are also strongly procyclical, whereas inflows into unem-

[35]See Elsby et al. (2015) for further details of this approach.

ployment are countercyclical. Finally, outflows into inactivity from both employment and unemployment are mildly procyclical.

A.3 Evidence from multinominal logistic regression

Table A.2 reports the coefficient estimates and associated standard errors from the estimation of the multinomial logistic regression specification based on equation (1) in the text. Each column features a specification where we control for additional characteristics, namely: age, gender, educational attainment, unemployment duration, and finally previous labour market status. The coefficients and standard errors from the final column are plotted in Figure 4 in the text. In addition to the coefficients we also report the Area Under Curve (AUC) statistic, which illustrates that in all cases these worker characteristics have predictive power regarding individual unemployment-to-inactivity transitions in the data.

Furthermore, we also test whether previous labour market status (i.e. Type 1 vs. Type 2 unemployment) has a significant impact on individual job finding rates, controlling for other observable characteristics. Following the same approach for estimating UN transition probabilities, we estimate the following logit model for job finding probability conditional on the same vector of worker characteristics:

$$\log\left(\frac{P(UE_i = 1|X_i)}{P(UE_i = 0|X_i)}\right) = \gamma_i + \mathbf{X}_i'\delta_i + \epsilon_i \tag{3}$$

The results are reported in Table A.3. Compared to labour market attachment (i.e. UN_i), we find that although previous labour force status is again a fairly strong predictor of individual job finding rates, our results suggest that in this case factors such as educational attainment (in particular having *some* schooling) and unemployment duration have even stronger predictive power.

Table A.2. Determinants of Labour Market Attachment

	(1) ME	(2) ME	(3) ME	(4) ME	(5) ME
Age:					
25-34	-0.267***	-0.301***	-0.257***	-0.235***	-0.0542
	(0.0321)	(0.0324)	(0.0315)	(0.0311)	(0.0294)
35-44	-0.179***	-0.222***	-0.184***	-0.153***	0.0430
	(0.0282)	(0.0288)	(0.0284)	(0.0281)	(0.0281)
45-54	-0.246***	-0.262***	-0.230***	-0.192***	0.0752*
	(0.0324)	(0.0320)	(0.0319)	(0.0324)	(0.0322)
>55	0.114**	0.177***	0.203***	0.247***	0.569***
	(0.0369)	(0.0388)	(0.0386)	(0.0384)	(0.0426)
Sex:					
Female		0.593***	0.599***	0.581***	0.407***
		(0.0252)	(0.0249)	(0.0255)	(0.0233)
Education:					
A-Level/Further			0.380***	0.394***	0.420***
			(0.0405)	(0.0405)	(0.0409)
GCSE			0.406***	0.438***	0.455***
			(0.0335)	(0.0341)	(0.0344)
Other/None			0.369***	0.415***	0.414***
			(0.0371)	(0.0370)	(0.0370)
Unemployment duration					
3-6 months				-0.191***	-0.186***
				(0.0318)	(0.0310)
6-12 months				-0.193***	-0.208***
				(0.0328)	(0.0310)
1-2 years				-0.210***	-0.256***
				(0.0351)	(0.0337)
>2 years				-0.246***	-0.297***
				(0.0351)	(0.0345)
Previous activity:					
Inactive					0.888***
					(0.0235)
Observations	97941	97941	97941	97941	97941
AUC	0.5368	0.5856	0.5933	0.5970	0.6493
AUC p-value	9.358e-52	2.30e-281	0.00	0.00	0.00

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table reports the average marginal effects and area under curve (AUC) statistics of logit estimators. Each specification also includes (quarterly) time fixed-effects, and clusters standard errors by time. In the full specification (5) we find that all worker characteristics we include are significant for determining labour market attachment. In all cases we strongly reject the null hypothesis that the AUC statistic is not different from 0.5. Source: LFS and authors' calculations.

Table A.3. Determinants of Individual Job Finding Rates

	(1)	(2)	(3)	(4)	(5)
Age	-0.0101***	-0.0101***	-0.0112***	-0.00354***	-0.00940***
	(0.000706)	(0.000701)	(0.000744)	(0.000620)	(0.000642)
Sex:					
Female		0.0542*	0.0246	-0.0751***	0.0353
		(0.0219)	(0.0219)	(0.0226)	(0.0226)
Educational attainment:					
Degree			-0.390***	-0.300***	-0.297***
			(0.0587)	(0.0508)	(0.0510)
No Degree			-0.888***	-0.708***	-0.722***
			(0.0523)	(0.0483)	(0.0485)
Other/None			-1.358***	-1.058***	-1.070***
			(0.0554)	(0.0526)	(0.0532)
Unemployment duration:					
3-6 months				-0.403***	-0.416***
				(0.0220)	(0.0221)
6-12 months				-0.715***	-0.717***
				(0.0274)	(0.0270)
1-2 years				-1.061***	-1.044***
				(0.0303)	(0.0301)
2+ years				-1.639***	-1.621***
				(0.0553)	(0.0543)
Previous employment status:					
Inactivity (Type 2)					-0.543***
					(0.0189)
Observations	98,286	98,286	98,286	98,286	98,286
AUC	0.5753	5761	0.6136	0.6803	0.6934
AUC p-value	9.38e-297	2.48e-302	0.00	0.00	0.00

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Notes: This table reports the average marginal effects and area under curve (AUC) statistics of logit estimators. Each specification also includes (quarterly) time fixed-effects, and clusters standard errors by time.

B Model Appendix

B.1 Timing

In the model time is discrete and runs forever. Within-period timing in the model is as follows.

Step 0: Stocks and productivity. At the beginning of period t aggregate labour productivity Z_t is revealed, based on the AR(1) process:

$$\ln Z_t = (1-\rho_z)\ln \bar{Z} + \rho_z \ln Z_{t-1} + \epsilon_t \tag{4}$$

where $\epsilon_t \sim \mathcal{N}(0, \sigma_z^2)$. The endogenous state variables are the beginning of period distribution of unemployed workers across both Type 1 and Type 2, and inactive workers $\{u_{1,t-1}, u_{2,t-1}, n_{t-1}\}$.

Step 1: Separations. Matches are exposed to a job-specific productivity shock drawn from distribution $G(a)$. After observing the value of the shock, firms and workers decide to continue the match based on whether the productivity draw is above the job destruction threshold, $a \geq \underline{a}_t$. Alongside this, a measure δ^x of existing matches separate for exogenous reasons unrelated to productivity. The overall separation rate is therefore $\delta_t = \delta^x + (1-\delta^x)G(\underline{a}_t)$. Workers who separate join the current period pool of searchers in the matching process. We assume that workers who separate endogenously will search for new matches with high enough search intensity to be classified as unemployed (i.e. they have higher labour market attachment). Workers who separate exogenously are assumed to search with low intensity below the threshold of active labour force participation. The resulting labour market stocks after separation shocks are given by:

$$\tilde{u}_{1,t} = u_{1,t-1} + (1-\delta^x)G(\underline{a}_t)(1-u_{t-1}-n_{t-1}) \tag{5}$$

$$\tilde{u}_t = \tilde{u}_{1,t} + u_{2,t-1} \tag{6}$$

$$\tilde{n}_t = n_{t-1} + \delta^x(1-u_{t-1}-n_{t-1}) \tag{7}$$

Step 2: Production. Production takes place and wages are paid to workers in active matches. Aggregate output is given by:

$$Y_t = (1-\tilde{u}_t-\tilde{n}_t)\cdot Z_t \frac{\int_{\underline{a}_t} a\,dG(a)}{1-G(\underline{a}_t)} \tag{8}$$

Step 3: Search. Searchers and vacancies match together via a constant returns aggregate matching function. New matches do not become productive until the next period. The number of searchers in the current period is given by $\tilde{s} = \tilde{u}_t + \tilde{n}_t$, and labour market tightness is defined as $\theta_t = v_t/(\tilde{u}_t + \tilde{n}_t)$. Aggregate search intensity $\tilde{e}_t$ is given by:

$$\tilde{e}_t = \tilde{u}_t \cdot \frac{\int_{\underline{e}} eF'(e)de}{1 - F(\underline{e})} + \tilde{n}_t \cdot \frac{\int^{\underline{e}} eF'(e)de}{F(\underline{e})} \tag{9}$$

where fluctuations are driven solely by changes in the composition of the non-employed. After matching has occurred, workers who are unsuccessful face the possibility of drawing a new search intensity e at a fixed Poisson arrival rate denoted by λ which differs by status. Post-matching labour market stocks are given by:

$$u_{1,t} = (1 - p_u(\tilde{e}_t, \theta_t))(1 - \lambda_{u_1} F(\underline{e}))\tilde{u}_{1,t} \tag{10}$$

$$u_{2,t} = (1 - p_u(\tilde{e}_t, \theta_t))(1 - F(\underline{e}))u_{2,t-1} + (1 - p_n(\tilde{e}_t, \theta_t))(1 - F(\underline{e}))\lambda_n \tilde{n}_t \tag{11}$$

$$u_t = u_{1,t} + u_{2,t} \tag{12}$$

$$n_t = (1 - p_u(\tilde{e}_t, \theta_t))F(\underline{e})(\lambda_{u_1}\tilde{u}_{1,t} + u_{2,t-1}) + (1 - p_n(\tilde{e}_t, \theta_t))(1 - \lambda_n + \lambda_n F(\underline{e}))\tilde{n}_t \tag{13}$$

B.2 Asset values

Below we outline the asset values associated with firms and workers that define the recursive structure of the labour market. For brevity of notation we indicate dependence on the aggregate state by the time subscript t.

Worker Bellman equations. The value of an employed worker is given by

$$\begin{aligned} W_t(a) \quad = \quad & w_t(a) + \beta \mathbb{E}_t \Bigg[(1 - \delta_{t+1}) \int_{\underline{a}_{t+1}} W_{t+1}(a') \frac{dG(a')}{1 - G(\underline{a}_{t+1})} \\ & + \delta^x \int^{\underline{e}} N_{t+1}(e') \frac{dF(e')}{F(\underline{e})} + (1 - \delta^x) G(\underline{a}_{t+1}) \int_{\underline{e}} U_{1,t+1}(e') \frac{dF(e')}{1 - F(\underline{e})} \Bigg] \end{aligned} \tag{14}$$

The above equation states that with probability $(1 - \delta_{t+1})$ the employment relationship continues to be productive in the next period. With probability δ^x, the worker will instead separate into inactivity in $t + 1$ and upon doing so draws a new value of e from the conditional distribution $F(e|e < \underline{e})$. With probability $(1 - \delta^x)G(\underline{a}_{t+1})$ the match separates endogenously due to the job-specific productivity shock and the individual becomes Type 1 unemployed next period, drawing a value from the conditional distribution $F(e|e \geq \underline{e})$.

The values associated with Type 1 and Type 2 unemployment are given by

$$\begin{aligned} U_{1,t}(e) &= b(e) + \beta \mathbb{E}_t \Bigg[p(e, \tilde{e}_t, \theta_t)(1 - \delta_{t+1}) \int_{\underline{a}_{t+1}} W_{t+1}(a') \frac{dG(a')}{1 - G(\underline{a})} \\ &+ \Big(1 - p(e, \tilde{e}_t, \theta_t)\Big)(1 - \lambda_{u_1}) U_{1,t+1}(e) \\ &+ p(e, \tilde{e}_t, \theta_t)(1 - \delta^x) G(\underline{a}_{t+1}) \int_{\underline{e}} U_{1,t+1}(e') \frac{dF(e')}{1 - F(\underline{e})} \\ &+ \lambda_{u_1} \Big(1 - p(e, \tilde{e}_t, \theta_t)\Big) \int_{\underline{e}} U_{1,t+1}(e') dF(e') \\ &+ \Big(\lambda_{u_1}(1 - p(e, \tilde{e}_t, \theta_t)) + p(e, \tilde{e}_t, \theta_t) \delta^x \frac{1}{F(\underline{e})}\Big) \int^{\underline{e}} N_{t+1}(e') dF(e') \Bigg] \end{aligned} \tag{15}$$

$$\begin{aligned} U_{2,t}(e) &= b(e) + \beta \mathbb{E}_t \Bigg[p(e, \tilde{e}_t, \theta_t)(1 - \delta_{t+1}) \int_{\underline{a}_{t+1}} W_{t+1}(a') \frac{dG(a')}{1 - G(\underline{a})} \\ &+ p(e, \tilde{e}_t, \theta_t)(1 - \delta^x) G(\underline{a}_{t+1}) \int_{\underline{e}} U_{1,t+1}(e') \frac{dF(e')}{1 - F(\underline{e})} \\ &+ \Big(1 - p(e, \tilde{e}_t, \theta_t)\Big) \int_{\underline{e}} U_{2,t+1}(e') dF(e') \\ &+ \Big(1 - p(e, \tilde{e}_t, \theta_t) + p(e, \tilde{e}_t, \theta_t) \delta^x \frac{1}{F(\underline{e})}\Big) \int^{\underline{e}} N_{t+1}(e') dF(e') \Bigg] \end{aligned} \tag{16}$$

and the value of inactivity is given by

$$\begin{aligned} N_t(e) &= b(e) + \beta \mathbb{E}_t \Bigg[p(e, \tilde{e}_t, \theta_t)(1 - \delta_{t+1}) \int_{\underline{a}_{t+1}} W_{t+1}(a') \frac{dG(a')}{1 - G(\underline{a})} \\ &+ p(e, \tilde{e}_t, \theta_t)(1 - \delta^x) G(\underline{a}_{t+1}) \int_{\underline{e}} U_{1,t+1}(e') \frac{dF(e')}{1 - F(\underline{e})} \\ &+ \lambda_n \Big(1 - p(e, \tilde{e}_t, \theta_t)\Big) \int_{\underline{e}} U_{2,t+1}(e') dF(e') \\ &+ (1 - \lambda_n)(1 - p(e, \tilde{e}_t, \theta_t)) N_{t+1}(e) \\ &+ \Big(\lambda_n(1 - p(e, \tilde{e}_t, \theta_t)) + p(e, \tilde{e}_t, \theta_t) \delta^x \frac{1}{F(\underline{e})}\Big) \int^{\underline{e}} N_{t+1}(e') dF(e') \Bigg] \end{aligned} \tag{17}$$

Firm Bellman equations. The asset value of a filled job is given by

$$J_t(a) \quad = \quad Z_t a - w_t(a) + \beta \mathbb{E}_t \left[(1-\delta_{t+1}) \int_{\underline{a}_{t+1}} J_{t+1}(a') \frac{dG(a')}{1-G(\underline{a}_{t+1})} + \delta_{t+1} V_{t+1} \right] \tag{18}$$

and the value associated with an unfilled vacancy is given by:

$$\begin{aligned} V_t \quad = \quad & -\kappa + \beta \mathbb{E}_t q(\tilde{e}_t, \theta_t)(1-\delta_{t+1}) \int_{\underline{a}_{t+1}} J_{t+1}(a') \frac{dG(a')}{1-G(\underline{a}_{t+1})} \\ & + \beta \mathbb{E}_t (1 - q(\tilde{e}_t, \theta_t)(1-\delta_{t+1})) V_{t+1} \end{aligned} \tag{19}$$

where $q(\tilde{e}_t, \theta_t)$ denotes the probability of filling a vacancy.

B.3 Equilibrium

Job creation. In equilibrium free entry implies that the value of an unfilled job is driven to zero in equilibrium:

$$V_t = 0$$

Imposing this condition in the Bellman equations for the firms yields the following job creation condition:

$$\frac{\kappa}{q(\tilde{e}_t, \theta_t)} = \beta \mathbb{E}_t \left[(1-\delta_{t+1}) \int_{\underline{a}_{t+1}} J_{t+1}(a') \frac{dG(a')}{1-G(\underline{a}_{t+1})} \right] \tag{20}$$

Wages. Wages are determined via Nash bargaining, which ensures that workers receive a fixed fraction $\eta \in (0,1)$ of the joint match surplus. The Nash wage satisfies the following equation:

$$\frac{\eta}{1-\eta} J_t(a) = W_t(a) - \left\{ \int_{\underline{e}} U_{1,t}(e') dF(e') + \int^{\underline{e}} N_t(e') dF(e') \right\} \tag{21}$$

Separations. The separation threshold for job-specific productivity $\underline{a}$ is defined as:

$$J_t(\underline{a}) = 0$$

Using the definition $J_t(a)$ we can define a recursive equation for $\underline{a}_t$:

$$0 = Z_t \underline{a}_t - w_t(\underline{a}_t) + \frac{\kappa}{q(\tilde{e}_t, \theta_t)} \tag{22}$$

Definition 1 (Equilibrium)**.** *An equilibrium with Nash bargained wages for a given realization of $\{Z_t\}_{t=0}^{T}$ and initial labour market stocks $\{u_{1,0}, u_{2,0}, n_0\}$ is defined as a reservation productivity $\underline{a}_t$, a wage schedule $w_t(a)$, labour market tightness θ_t, aggregate search intensity $\tilde{e}_t$, aggregate labour market stocks $\{u_{1,t}, u_{2,t}, n_t\}$, and the value functions $J_t(a)$, $W_t(a)$, $U_{1,t}(e)$, $U_{2,t}(e)$ and $N_t(e)$ which satisfy (i) the laws of motion in (5)-(13), (ii) the value functions defined in (14)-(18), (iii) the job creation condition in (20), (iv) the Nash sharing rule in (21), and (v) the separation threshold condition in (22).*

B.4 Model solution

We solve the model by log-linearly approximating around the steady state. When obtaining a linearized solution to the model we need to keep track of several integrals that do not in general have closed form expressions, namely $\int_{\bar{a}_t} a dG(a)$, $\int_{\bar{e}} eU_{1,t}(e)dF(e)$ and $\int^{\bar{e}} eN_t(e)dF(e)$. To overcome this issue we take local approximations to these integrals.

A first-order Taylor expansion of $\tilde{a}_t = \int_{\bar{a}_t} a dG(a)$ gives:

$$\tilde{a}_t \approx \tilde{a} - \bar{a}g(\bar{a})(\bar{a}_t - \bar{a})$$

Taking a Taylor approximation of the remaining integrals:

$$\int^{\bar{e}} eN_t(e)dF(e) \approx \int^{\bar{e}} eN(e)dF(e) + \int^{\bar{e}} edF(e) \cdot \Big[N_t(e) - N(e)\Big]$$

Integrating again between $[0, \bar{e}]$ and rearranging allows us to write:

$$\int^{\bar{e}} eN_t(e)dF(e) \approx \int^{\bar{e}} eN(e)dF(e) + \frac{\int^{\bar{e}} edF(e)}{F(\bar{e})}\Big[\tilde{N}_t - \tilde{N}\Big]$$

where $\tilde{N}_t = \int^{\bar{e}} N_t(e)dF(e)$. By exactly the same argument we can also write:

$$\int_{\bar{e}} eU_{1,t}(e)dF(e) \approx \int_{\bar{e}} eU_1(e)dF(e) + \frac{\int_{\bar{e}} edF(e)}{1 - F(\bar{e})}\Big[\tilde{U}_{1,t} - \tilde{U}_1\Big]$$

where $\tilde{U}_{1,t} = \int_{\bar{e}} U_{1,t}(e)dF(e)$.

B.5 Parameterization

The model is parameterized at a quarterly frequency. Where possible, the model parameters are calibrated in a way that is consistent with standard parameter values that are routinely used in the wider literature on quantitative search & matching models. Otherwise parameters are set to match key observable moments in the data. The resulting parameter values are summarized in Table B.1. The accompanying steady state fit of the model is reported in Table 4

Functional forms. We assume that the search intensity distribution $F(e)$ and job-specific productivity distribution $G(a)$ are both log-normal, with parameters $\{\mu_F, \sigma_F\}$ and $\{\mu_G, \sigma_G\}$ respectively. For the flow utility associated with non-employment $b(e)$, we assume two distinct values $\{b_U, b_N\}$ corresponding to unemployment and inactivity. Finally, for matching we follow Pissarides (2000) and assume that the job finding probability for a non-employed worker with search intensity e is given by (we omit the t subscripts):

$$p(e, \tilde{e}, \theta) = e \cdot M \left(\frac{\theta}{\tilde{e}} \right)^{1-\alpha}$$

where M is a matching efficiency constant and $\alpha > 0$ is the elasticity of new matches with respect to searchers. The corresponding job filling probability for a firm posting a vacancy is given by:

$$q(\tilde{e}, \theta) = M \left(\frac{\tilde{e}}{\theta} \right)^{\alpha}$$

This choice of functional form, where the individual job finding probability is increasing proportionally in search effort e, i.e. $p(e, \tilde{e}, \theta) = e \cdot p(\tilde{e}, \theta)$, together with a time-invariant participation threshold $\underline{e}$ and search intensity distribution $F(e)$, ensures that the ratio of the NE and UE flows are constant (as in the data). To see this, note that the average job finding probabilities an inactive and unemployed workers (respectively) are given by:

$$p_n(\tilde{e}, \theta) = \frac{\int^{\underline{e}} eF'(e)de}{F(\underline{e})} \cdot M \left(\frac{\theta}{\tilde{e}} \right)^{1-\alpha}$$

$$p_u(\tilde{e}, \theta) = \frac{\int_{\underline{e}} eF'(e)de}{1 - F(\underline{e})} \cdot M \left(\frac{\theta}{\tilde{e}} \right)^{1-\alpha}$$

Hence the ratio of the employment inflow rates is constant in the model (denoted by χ):

$$\frac{p_n(\tilde{e},\theta)}{p_u(\tilde{e},\theta)} = \frac{\int^{\underline{e}} eF'(e)de}{\int_{\underline{e}} eF'(e)de} \cdot \frac{1-F(\underline{e})}{F(\underline{e})} = \chi$$

Externally calibrated parameters. Beginning with the deep parameters that are treated as structural, we set the discount factor $\beta = 0.99$ and workers' relative bargaining strength $\eta = 0.5$ (implying symmetric Nash bargaining), values which are commonly used in the literature. The means of the idiosyncratic shock distributions G and F, as well as tightness θ and the steady state level of aggregate productivity A, are all normalised.[36] We set the values of the aggregate labour productivity process $\{\rho_z, \sigma_z\}$ to match the observed serial correlation and volatility of labour productivity in the data. We set the standard deviation of search intensity among the non-employed $\sigma_F =$ based on estimated distribution of search intensity using the LFS following the approach outlined in Section 3.

The elasticity of the matching function α is obtained via estimation of a log-linear version of the matching function:

$$\log(h_t) = \log(M_t) + (1-\alpha)\log(\theta_t) + \epsilon_t \tag{23}$$

where h_t denote new hires in period t. In the absence of data on search effort $\tilde{e}_t$ we treat this as an unobserved state variable which is instead absorbed by allowing for time-varying matching efficiency M_t in the estimation.[37] We estimate the above specification using a Kalman filter as in Pizzinelli and Speigner (2017), which results in an estimated elasticity $\hat{\alpha} = 0.7$.[38]

Targets. We set several parameters in order to match the average flow rates in the LFS. We set the (constant) EN rate in the model δ^x directly to match the empirical counterpart. Given this, we then target the steady state share of jobs destroyed endogenously $G(\underline{a})$ to match the empirical separation rate into unemployment. We set the exogenous participation threshold value of search intensity $\underline{e}$ to match the ratio of the NE and UE

[36] This normalisation does not influence the model's equilibrium properties.

[37] Given that total hires in the model are given by $h_t = \tilde{s}_t \mu_F M \left(\frac{\theta_t}{\tilde{e}_t}\right)^{1-\alpha}$, the log-linear version of the matching function is:

$$\log(h_t) = \log(\tilde{s}_t) + \log\mu_F + \log M - (1-\alpha)\log(\tilde{e}_t) + (1-\alpha)\log(\theta_t)$$

In practice, in the estimation we are defining the unobserved state as $M_t = \frac{\tilde{s}_t \mu_F M}{\tilde{e}_t^{1-\alpha}}$, so M_t is really capturing fluctuations in the number of searchers $\tilde{s}_t$ and aggregate search intensity $\tilde{e}_t$.

[38] For more details on the matching function estimation methodology see Pizzinelli and Speigner (2017).

Table B.1. Summary of parameters

Parameter	Value	Description	Source/Target
Assigned:			
β	0.99	Discount factor	Standard
η	0.72	Worker bargaining power	Standard
μ_F	0	Mean of search intensity distribution	Normalization
μ_G	0	Mean of productivity distribution	Normalization
θ	1	Steady state tightness	Normalization
Z	1	Steady state aggregate productivity	Normalization
σ_F	1.0323	Std. dev. of search intensity distribution	ONS
ρ_z	0.7079	Persistence of aggregate productivity	ONS
σ_z	0.0051	Std. dev. of aggregate productivity	ONS
α	0.72	Matching function elasticity	Estimated
Calibrated:			
δ^x	0.019	Exogenous separation rate	$EN = 0.019$
$G(\underline{a})$	0.012	Share of destroyed matches	$EU = 0.012$
$\underline{e}$	0.999	Participation threshold	$\chi = 0.2127$
λ_{u_1}	0.1676	Type 1 unemp. persistence	$UN = 0.182$
λ_n	0.0902	Inactivity persistence	$NU = 0.047$
M	0.0690	Match efficiency	$UE = 0.268$
$F(\underline{e})$	0.4549	Inactivity draw probability	$\frac{u_2}{u} = 0.57$
b_u	5.1213	Unemployment flow value	$b_U \frac{\tilde{u}}{\tilde{u}+\tilde{n}} + b_N \frac{\tilde{n}}{\tilde{u}+\tilde{n}} = 0.7$
σ_G	0.1623	Std. dev. of productivity distribution	$\sigma_{EU} = 0.091$
Implied:			
κ	0.0021	Vacancy cost	
b_N	-0.0121	Inactive flow value	

rates in the model, given by χ above. The arrival probabilities of idiosyncratic shocks to search intensity $\{\lambda_{u_1}, \lambda_n\}$ are set to match the observed flow rates between inactivity and unemployment (i.e. the UN and NU rates). The matching efficiency constant M is set to target the average UE rate. Additionally, we set the probability of drawing a search intensity shock under the threshold $F(\underline{e})$ such that 57% unemployed workers on average are Type 2, as in the LFS data. The flow value b_u is set such that the average flow value of non-employment is equal to 0.71, following Hall and Milgrom (2008). Finally, to calibrate the standard deviations of the job-specific productivity distribution σ_G we target the observed volatility in the EU rate. The remaining parameters, the flow cost of posting a vacancy κ and the flow value of inactivity b_N, are then implied by the remaining steady state conditions of the model.

Small surplus. The small surplus calibration strategy we use is essentially the same as outlined above, but with two key differences following Hagedorn and Manovskii (2008): (i) we set the worker bargaining power $\eta = 0.052$, and (ii) we target an average flow value of non-employment equal to 0.955. We also recalibrate the value of σ_G to still be consistent with σ_{EU}, which requires $\sigma_G = 0.7126$.

Rigid wages. We also analyse a version of the model where we allow for wage rigidity by specifying an ad hoc rule which ensures worker bargaining power is countercyclical, following the approach taken in Jung and Kuester (2015). This is convenient in an environment with endogenous job destruction and Nash wages, as this allows the separation margin to remain tractable whilst ensuring all separations are bilaterally efficient. More specifically, we impose that worker bargaining power η_t evolves according to:

$$(1 - \eta_t) = (1 - \eta) \cdot \exp\{\gamma_w Z_{t-1}\}$$

We then jointly set $\{\sigma_G, \gamma_w\}$ to target $\{\sigma_{EU}, \sigma_{UE}\}$. This results in values $\sigma_G = 0.4543$, $\gamma_w = 2.4850$, though overall the model in this case has difficulty matching both the separation and job finding margins.

DMP model with no search intensity. In Section 4 we employ a version of our baseline model where heterogeneity in search intensity among the non-employed is shut down, i.e. $\sigma_F = 0$ and $e = 1$. For the purposes of this exercise we try to keep as many of the parameters as possible the same. Specifically, we maintain the same values for the externally calibrated parameters $\{\beta, \eta, \alpha, \rho_z, \sigma_z\}$, as well as the the standard deviation of job-specific productivity σ_G and the share of matches which separate $G(\underline{a})$. We then choose values for $\{M, b_U, \kappa\}$ which are consistent with the steady state levels of employment and the vacancy filling rate from our baseline calibration.

C Additional Tables and Figures

C.1 Additional Figures

Figure C.1. Actual and Counterfactual UN rate (incl. social welfare recipients)

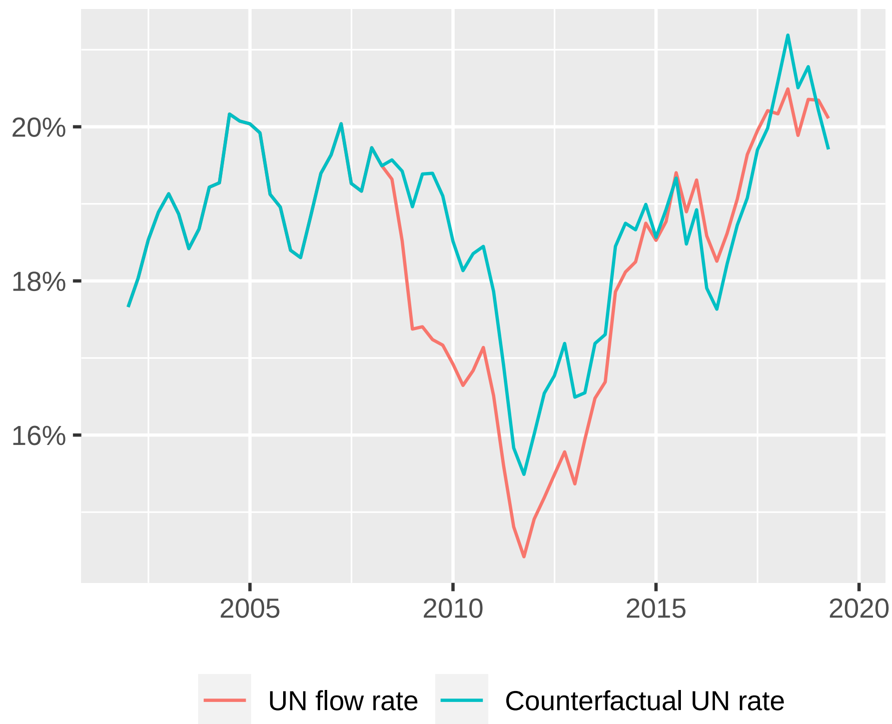

Figure C.2. UN rate for Type 2: Role of benefit recipients

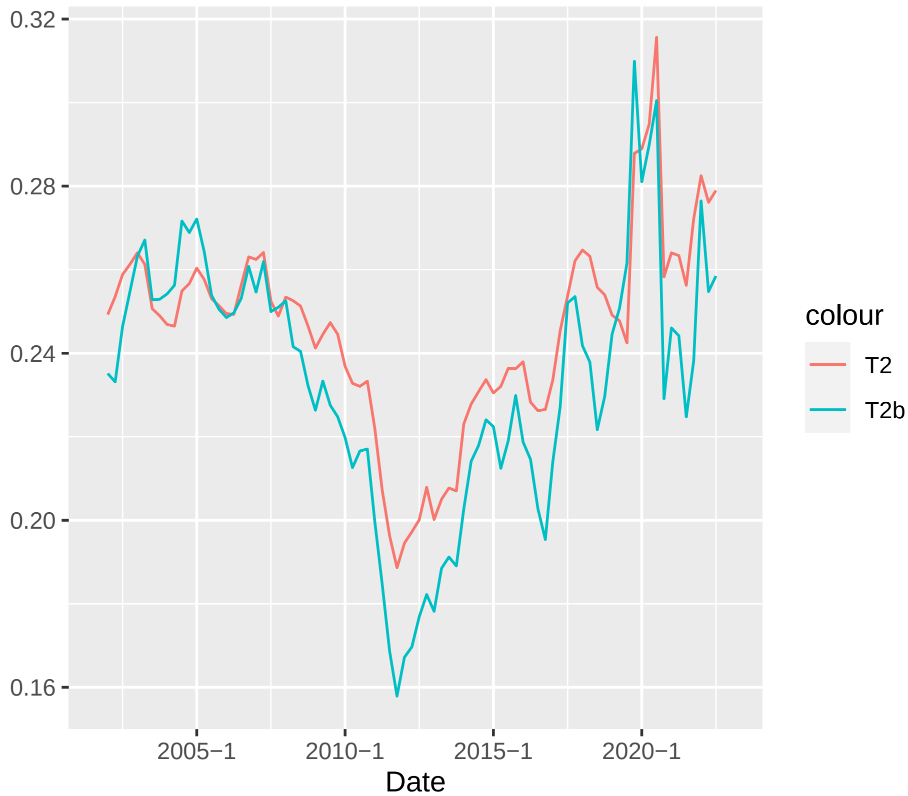

Figure C.3. Response of stocks to a productivity shock in the calibrated model. Expressed as log deviations from steady state levels.

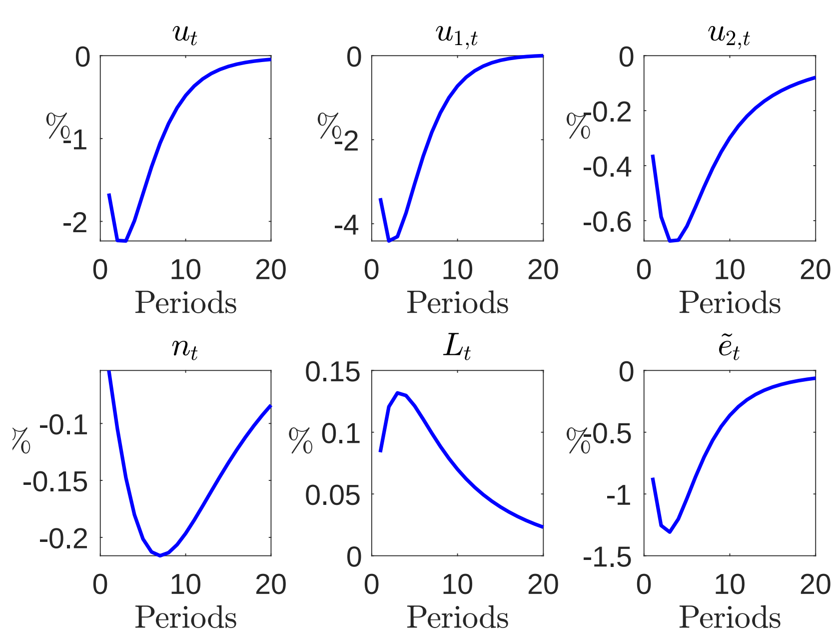

Figure C.4. Labour market flows in the Great Recession: Data vs Model

C.2 Additional Tables

Table C.1. Transition Rates: Model

State in t	Transition Probability	State in $t+1$
l	$1-\delta_{t+1}$	l
l	$(1-\delta^x)G(\underline{a}_{t+1})$	u_1
l	0	u_2
l	δ^x	n
u_1	$p_u(\theta_t)(1-\delta_{t+1})$	l
u_1	$(1-p_u(\theta_t))(1-\lambda_{u_1}F(\underline{e}))+p_u(\theta_t)(1-\delta^x)G(\underline{a}_{t+1})$	u_1
u_1	0	u_2
u_1	$(1-p_u(\theta_t))\lambda_{u_1}F(\underline{e})+p_u(\theta_t)\delta^x$	n
u_2	$p_u(\theta_t)(1-\delta_{t+1})$	l
u_2	$p_u(\theta_t)(1-\delta^x)G(\underline{a}_{t+1})$	u_1
u_2	$(1-p_u(\theta_t))(1-F(\underline{e}))$	u_2
u_2	$(1-p_u(\theta_t))F(\underline{e})+p_u(\theta_t)\delta^x$	n
n	$p_n(\theta_t)(1-\delta_{t+1})$	l
n	$p_n(\theta_t)(1-\delta^x)G(\underline{a}_{t+1})$	u_1
n	$(1-p_n(\theta_t))\lambda_n(1-F(\underline{e}))$	u_2
n	$(1-p_n(\theta_t))(1-\lambda_n+\lambda_nF(\underline{e}))+p_n(\theta_t)\delta^x$	n

Table C.2. Cyclical properties: Model vs. Data

	Flows						Stocks		
	EU	EN	UE	UN	NE	NU	E	U	LFPR
Panel A. Data									
std(x)	0.091	0.066	0.061	0.065	0.070	0.051	0.006	0.062	0.002
corr(x, Y)	-0.605	0.172	0.535	0.219	0.496	-0.256	0.737	-0.771	0.243
corr(x, x_{-1})	0.359	-0.194	0.489	0.238	0.307	0.106	0.855	0.884	0.651
Panel B. Baseline									
std(x)	0.092	0.00	0.006	0.019	0.006	0.001	0.002	0.032	0.001
corr(x, Y)	-0.970	0.00	0.970	0.949	0.970	-0.9701	0.827	-0.924	0.334
corr(x, x_{-1})	0.548	-	0.548	0.804	0.548	0.548	0.850	0.822	0.928
Panel C. Small surplus									
std(x)	0.199	0.00	0.010	0.042	0.010	0.003	0.004	0.069	0.001
corr(x, Y)	-0.955	0.00	0.955	0.967	0.955	-0.955	0.911	-0.969	0.442
corr(x, x_{-1})	0.548	-	0.548	0.801	0.548	0.548	0.849	0.822	0.930
Panel D. Rigid wages									
std(x)	0.110	0.00	0.0105	0.022	0.0105	0.002	0.002	0.040	0.001
corr(x, Y)	-0.945	0.00	0.945	0.956	0.945	-0.945	0.864	-0.950	0.458
corr(x, x_{-1})	0.548	-	0.548	0.814	0.548	0.548	0.853	0.822	0.924

Notes: Simulated data are logged and HP filtered using smoothing parameter $\lambda = 1600$. Each replication computes simulated statistics from a sample of 120 quarterly observations. Reported statistics are averages over 100 replications.