Received: 26 January 2021 | Revised: 28 March 2023 | Accepted: 17 May 2023

DOI: 10.1002/ijfe.2845

RESEARCH ARTICLE

WILEY

Labour reallocation and unemployment fluctuations: A tale of two tails

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Abstract

This paper examines the sectoral shifts hypothesis for the US regional labour market using a quantile panel framework. We use a monthly panel dataset that spans over 1990–2016 for the 48 US states and employ a dynamic quantile panel data regression approach to investigate the asymmetric nature of the relationship between sectoral labour reallocation and unemployment fluctuations. The empirical evidence suggests that the impact of the employment dispersion index is relatively small and insignificant for lower levels of unemployment but becomes positive and highly significant for higher rates. Our findings bear out the asymmetry of reallocation disturbances for the US labour market.

KEYWORDS

dynamic panel data, labour reallocation, quantile regression, sectoral shifts, unemployment

1 | INTRODUCTION

The global financial crisis 2007–2009 and the COVID-19 recession have triggered a renewed interest in the macroeconomics of intersectoral and intrasectoral movement of resources.[1] This article focuses on intersectoral labour reallocation and extends previous efforts by encompassing multiple dimensions within a unified non-linear framework for the analysis of the sectoral shifts hypothesis (SSH henceforth). It analyses simultaneously both the regional and sectoral characteristics of labour reallocation through a panel quantile regression (PQR) framework.

The SSH asserts that the reallocation of workers from declining sectors to expanding sectors requires time and thus entails a temporary increase in unemployment (Lilien, 1982). A vast body of work has emerged to explore the impact of labour reallocation on unemployment (see Gallipoli & Pelloni, 2013). Within this vast body of literature, a significant, but relatively smaller, component has investigated sectoral shifts in the regional perspective. Recent works (Bakas et al., 2016, 2017; Simon, 2014; among others) have revisited previous efforts by incorporating up to date developments in panel data econometrics regarding dynamics, heterogeneity, and cross-sectional dependence.

As with most works in this field, these contributions have employed a linear regression (LR) framework, thus focusing on the conditional mean response under the assumption of symmetry. Such an approach disregards the non-directional, non-linear, and asymmetrical nature of idiosyncratic shocks. To test and measure sectoral shifts in a consistent manner it is necessary to consider the impact of the shocks over the whole unemployment conditional distribution. It is the purpose of the current paper to address this issue while simultaneously taking into account the regional dimension. We, thus, examine the impact of intersectoral labour reallocations on unemployment for the US regional labour market within a PQR. Our framework allows us to examine the entire conditional distribution of unemployment while taking into consideration both the sectoral and regional dimensions of the data.

This paper provides a comprehensive structure to explore the SSH at the regional level. Its contribution is fourfold: first, we employ a dynamic quantile panel framework, that accounts for the regional and sectoral dimensions of labour reallocation. This modelling strategy allows us to observe the relative importance of sectoral reallocation across the conditional distribution of the unemployment rate rather than focusing exclusively on its conditional mean. To the best of our knowledge, this is the first study that examines the sectoral shifts hypothesis in a quantile panel setting. Second, we consider recent developments in quantile regression techniques for panel data. Third, we extend the information set used in previous studies by considering additional control variables, such as the state house price index, the world oil price, the US effective exchange rate, the economic policy uncertainty measure, and the S&P500 stock market index and its volatility. Fourth, we explore the impact of sectoral reallocation on the Hornstein-Kudlyak-Lange (HKL henceforth) non-employment index (Hornstein et al., 2014) as well as the US aggregate unemployment rate in addition to the state levels.

Our results confirm the positive and significant effect of labour reallocation on US unemployment at the state level and show that the relationship is not symmetric. The impact of the Lilien's employment dispersion index is relatively small and insignificant for lower levels of unemployment while it becomes larger and highly significant for higher levels of (the conditional distribution) unemployment. This outcome corroborates the hypothesis that it is the size of the sectoral shocks that matters. Furthermore, it upholds the asymmetry of reallocation disturbances. These findings are robust to a series of robustness checks, including alternative measures of reallocation, alternative indices for unemployment, various control variables, and alternative panel quantile estimation methods. This study provides a new set of results and insights about labour reallocation in regional labour markets, which had eluded previous work.

The remainder of the paper is organised as follows. Section 2 outlines briefly the topic background. Section 3 presents the data and discusses the econometric methodology. Section 4 reports the empirical results, while Section 5 presents the robustness checks. Finally, Section 6 provides our concluding remarks.

2 | BACKGROUND

Lilien (1982), building on Lucas and Prescott (1974), suggests that exogenous changes in the dispersion of relative prices could raise the speed of intersectoral labour reallocation and increase aggregate unemployment as an input into a search technology. Since spells of relatively high unemployment could reflect episodes of increased dispersion in employment demand, Lilien measured the correlation between US unemployment rate (u) and the weighted standard deviation of cross-sectoral employment growth rates (σ), the so-called Lilien's dispersion proxy.

The pioneering effort of Lilien triggered a research agenda on the macroeconomic effects of labour reallocation and inspired the subsequent job reallocation field of inquiry (see Gallipoli & Pelloni, 2013, for a survey). Empirical explorations of Lilien's hypothesis have been following diverse paths characterised by their econometric methodologies and/or the level of simultaneous disaggregation of relevant characteristics.

An important strand of this literature focused on the regional and sectoral dimensions simultaneously (Blanchard & Katz, 1992; Garonna & Sica, 2000; Jackman & Roper, 1987; Keane, 1993; Keane & Prasad, 1996; Medoff, 1983; Neumann & Topel, 1991; Newell & Pastore, 2006; Robson, 2009 and Shaw, 1989). These studies were constrained by the relevant limited samples that were available at that time and the use of Fixed Effects (FE) estimators in the case of a panel data analysis. Furthermore, they were all rooted in a linear framework and conveyed the effects of changes in the covariates on the conditional mean function. These analytical features reflected the state of the art at the time these studies were carried out. Given recent advances in panel data econometrics, Bakas et al. (2016, 2017) have gone beyond the limitations of FE estimation and were able to account for heterogeneity, spillover effects and common factors in a more complete way.

Measurement of the impact of sectoral shocks through LR modelling implies loss of potentially relevant information (Panagiotidis & Pelloni, 2014). LR results ignore the asymmetric and non-directional character of allocative shocks. A LR model could work satisfactorily for aggregate shocks. This class of disturbances is directional (positive/negative) in its nature. Thus, aggregate shocks, through the appropriate propagation mechanism, could generate large aggregate fluctuations independently of their size. The change in the central location of the relevant macro-variable distribution should convey sufficient information about the impact of the shock. The characterising feature of allocative shocks is profoundly different. These disturbances influence unemployment if and only if they are unfavourable to the existing allocation of resources. A change in demand composition requires a reallocation of workers and so unemployment, as a search technology input, will increase. It is the magnitude of the reallocations, which determines the aggregate response. Small allocative shocks generate a small unemployment response while large shocks generate a large rise in unemployment. The size of the shock and its asymmetric structure are the relevant traits in this analytical context.

The implication of these stylized characteristics is that the conditional unemployment distribution is negatively skewed, and the mass of the distribution is concentrated on the right: the effects of employment reallocations on the lower unemployment quantiles are small and insignificant while they are large for the upper quantiles. Panagiotidis and Pelloni (2014) have pointed out the shortcomings of LR modelling of sectoral shifts and updated Lilien's analysis of the ($u-\sigma$) correlation through a QR approach aimed at measuring and testing the asymmetry's influence.[2] Their analysis corroborated Lilien's outcomes but relied on a one-dimensional characteristic (sector) as it was an aggregate time series approach. This paper extends the analysis in a panel setting, by considering a simultaneous disaggregation along two dimensions: sector and region.

We maintain that the two main stylized characteristics of reallocation unemployment are the size of the shock and the asymmetric unemployment response. An LR framework could deal with the dimensionality property via a polynomial representation of the dispersion proxy but would only capture the impact on the conditional mean. An LR model cannot handle the asymmetric properties of the unemployment distribution. We model simultaneously the sectoral and regional dimensions via PQR for a monthly dataset of the US regional labour market. A PQR approach to the sectoral shifts hypothesis is fully representative of the hypothesis fundamental features. It has never been attempted before and could provide critical information for further developments of the hypothesis both at an empirical and theoretical level.

3 | DATA AND METHODOLOGY

Using monthly pooled time-series-cross-section data for the 48 contiguous US states over the period 1990:M02 to 2016:M12 (i.e., $N = 48$ and $T = 323$, compiling a rich dataset of 15,504 observations) and in order to explore the heterogeneous effects of sectoral labour reallocation at different levels of unemployment, we employ a conditional quantile dynamic panel data model, where we allow the coefficients to vary across quantiles (τ), as follows[3,4]:

$$Q_\tau(U_{i,t}|U_{i,t-1},\sigma_{i,t},z_{i,t},w_t,\mu_i) = \alpha^{(\tau)}U_{i,t-1} + \beta^{(\tau)}\sigma_{i,t} + \varphi'^{(\tau)}z_{i,t} + \lambda'^{(\tau)}w_t + \mu_i, \tag{1}$$

where $Q(\cdot|\cdot)$ is the τ*-th* conditional quantile function of US state unemployment, $U_{i,t}$ is the measure of unemployment for the state i at time t; $\sigma_{i,t}$ is the measure of employment cross-sectoral dispersion; the vector $\boldsymbol{z_{i,t}}$ is a vector of state-specific control variables, where we include the state personal income growth, $\Delta lnPI_{i,t}$; the vector of aggregate factors $\boldsymbol{w_t}$ represents common control variables that capture aggregate demand shocks, common to all states, encompassing the federal funds rate growth, ΔFR_t, its variability (derived from a GARCH (1,1) model), HFR_t, and the local government expenditures growth, ΔlnG_t; and μ_i denotes a set of state fixed effects capturing the influence of unobserved state-specific heterogeneity.[5]

We also explore the robustness of our main results using an extended version of Equation (1). Thus, in vector $\boldsymbol{z_{i,t}}$ we include also the state house price index growth, $\Delta lnHPI_{i,t}$, which captures the regional house price market; while in vector $\boldsymbol{w_t}$ we account for the crude oil price growth, $\Delta lnOIL_t$, to quantify aggregate supply shocks, the US effective exchange rate growth, $\Delta lnEER_t$, which accounts for the exchange rate shocks, and the economic policy uncertainty index, $lnEPU_t$, that accounts for fluctuations of economic policy making in the US. Furthermore, we augment Equation (1) by adding as covariates (in vector $\boldsymbol{w_t}$), the return of the S&P500 stock market index ($\Delta lnSP_t$) and its realised volatility ($SPRV_t$) to control for financial sector's shocks.

The employment and unemployment per state series were obtained from the US Bureau of Labour Statistics (BLS), while the state-specific control variables were downloaded from the US Bureau of Economic Analysis (BEA) and the Freddie May house index database, respectively. Finally, all aggregate (*common to all states*) series were collected from the Federal Reserve Economic Data (FRED) database.

As a further robustness check and an extension of our findings, we re-estimate Equation (1) with the aggregate US unemployment rate (U_t^{US}) and the non-employment index (NEI_t) as the dependent variable.[6] The NEI index is an alternative to the standard unemployment rate measure (Hornstein et al., 2014). It is a weighted average of the different subclasses of unemployed individuals and workers out of the labour force. The weight of each subgroup is the sample average of its job-finding rate relative to the job-finding rate of the short-term unemployed. Thus, the NEI index includes additional segments of non-employed workers and accounts for their employability.

The employment dispersion measure (Lilien, 1982) for each state i at month t, $\sigma_{i,t}$, is calculated as the weighted standard deviation of the cross-sectoral employment growth rates as follows:

$$\sigma_{i,t} = \left[\sum_{j=1}^{K}\left(N_{j,i,t}/N_{i,t}\right)\left(\Delta\ln N_{j,i,t} - \Delta\ln N_{i,t}\right)^2\right]^{1/2} \tag{2}$$

TABLE 1 Summary statistics.

Variables	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
State-specific						
Un. Rate	5.618	1.864	2.100	14.900	0.975	4.191
U^{log}	−2.873	0.341	−3.842	−1.742	0.119	2.854
U^{ln}	−2.931	0.322	−3.863	−1.904	0.065	2.821
sigma (σ^{9})	0.005	0.003	0.000	0.047	3.219	25.530
sigma (σ^{10})	0.005	0.003	0.000	0.046	3.006	21.679
sigma (σ^{13})	0.005	0.004	0.001	0.085	5.401	72.325
ΔlnPI	0.004	0.004	−0.024	0.038	−0.256	8.514
ΔlnHPI	0.003	0.005	−0.035	0.037	−0.661	8.563
Common to all states						
Un. Rate^{US}	5.933	1.617	3.800	10.000	1.091	3.132
NEI	8.960	0.857	7.671	11.029	0.764	2.696
ΔFR	−0.024	0.175	−0.960	0.530	−1.570	8.351
HFR	0.054	0.120	0.004	1.150	4.853	33.777
ΔlnG	0.004	0.004	−0.010	0.026	0.856	7.520
lnEPU	4.624	0.295	4.047	5.502	0.428	2.491
ΔlnEER	0.000	0.017	−0.048	0.065	0.046	3.510
ΔlnOIL	0.003	0.086	−0.337	0.377	−0.314	4.916
ΔlnSP	0.006	0.042	−0.186	0.106	−0.779	4.762
SPRV	0.031	0.055	0.002	0.653	6.908	65.797

Note: Descriptive statistics for the full sample of 15,504 observations, based on $N = 48$ and $T = 323$. *Un. Rate* is the US state level unemployment rate, while U^{log} is the logistic transformation of the state's unemployment rate and U^{ln} is its logarithmic transformation. *Sigma* ($\sigma^{9}/\sigma^{10}/\sigma^{13}$) is the labour reallocation index for the 9/10/13 sectors of the economy, respectively. *ΔlnPI* is the state's personal income growth, while *ΔlnHPI* is the state's house price index growth. *Un. Rate*^{US} is the aggregate US unemployment rate, while *NEI* is the US non-employment index. *ΔFR* the federal funds rate growth, while *HFR* is the variability of the federal funds rate. Finally, *ΔlnG* is the government expenditures growth, *lnEPU* is the logarithm of the US economic policy uncertainty index, *ΔlnEER* is the US effective exchange rate growth, *ΔlnOIL* is the crude oil price growth, *ΔlnSP* is the return of the S&P500 stock market index while *SPRV* is the realised volatility of the S&P500 index.

where $N_{j,i,t}$ is the employment in sector j for state i at month t, $N_{i,t}$ is aggregate employment at month t for state i, K is the number of sectors (with $j = 1, 2, \ldots, K$ sectors) in the state i, and $N_{j,i,t}/N_{i,t}$ is the relative size of sector j over the total regional employment at month t.[7]

The reallocation index ($\sigma_{i,t}$), following Bakas et al. (2017), is computed using the shares of the available sectoral decomposition of monthly employment for each state on the following sectors: (1) mining-logging-construction, (2) manufacturing (with a further disaggregation on durable and nondurable goods), (3) trade-transportations (with a further disaggregation on wholesale trade, retail trade, and transportations), (4) information, (5) financial activities, (6) professional activities, (7) education-health, (8) leisure-hospitality, (9) other services, and (10) government sector. Using this industrial decomposition, we compute measures of dispersion allowing for alternative sectoral disaggregation (9, 10 and 13 sectors respectively).[8]

Table 1 presents the descriptive statistics for the unemployment series, the sectoral shifts measures, the state-specific control variables, and the aggregate control variables that are used in our analysis. The relative low average level of the aggregate unemployment rate for the US over this period (with a mean value of 5.93%) is evident in this table. However, there is a notable variation across states over this period (from a minimum of state level unemployment rate of 2.1% to a maximum of 14.9%). In addition, we can observe that the mean values of the alternative measures of the labour reallocation index, based on the 9, 10 and 13 sectors decomposition, are similar, however they differ considerably on their maximum values. Also, note the high level of kurtosis of σ that signals fat tails (a characteristic that the linear framework cannot capture).

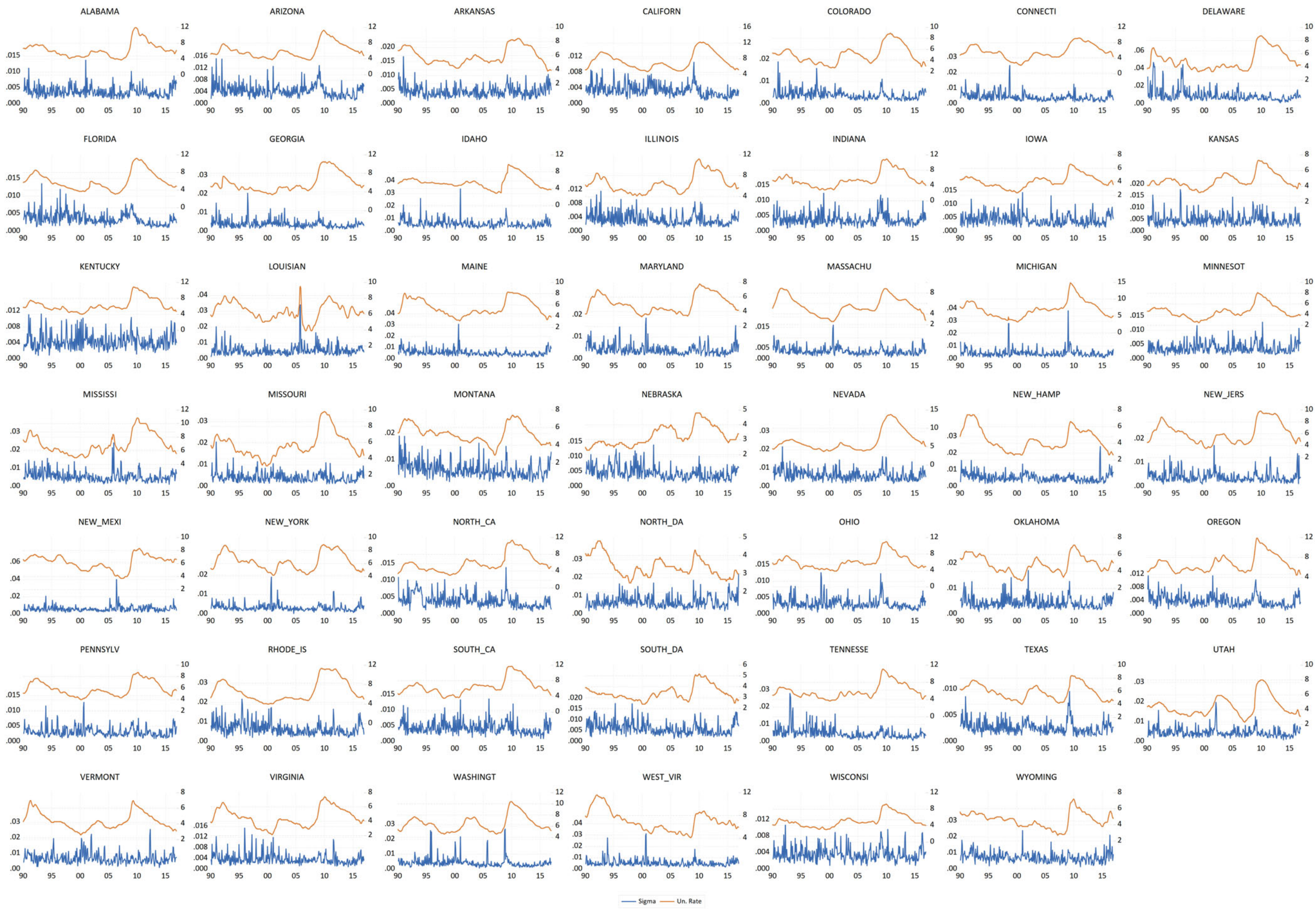

FIGURE 1 Unemployment rate and labour reallocation index – 48 US States over 1990–2016. [Colour figure can be viewed at wileyonlinelibrary.com]

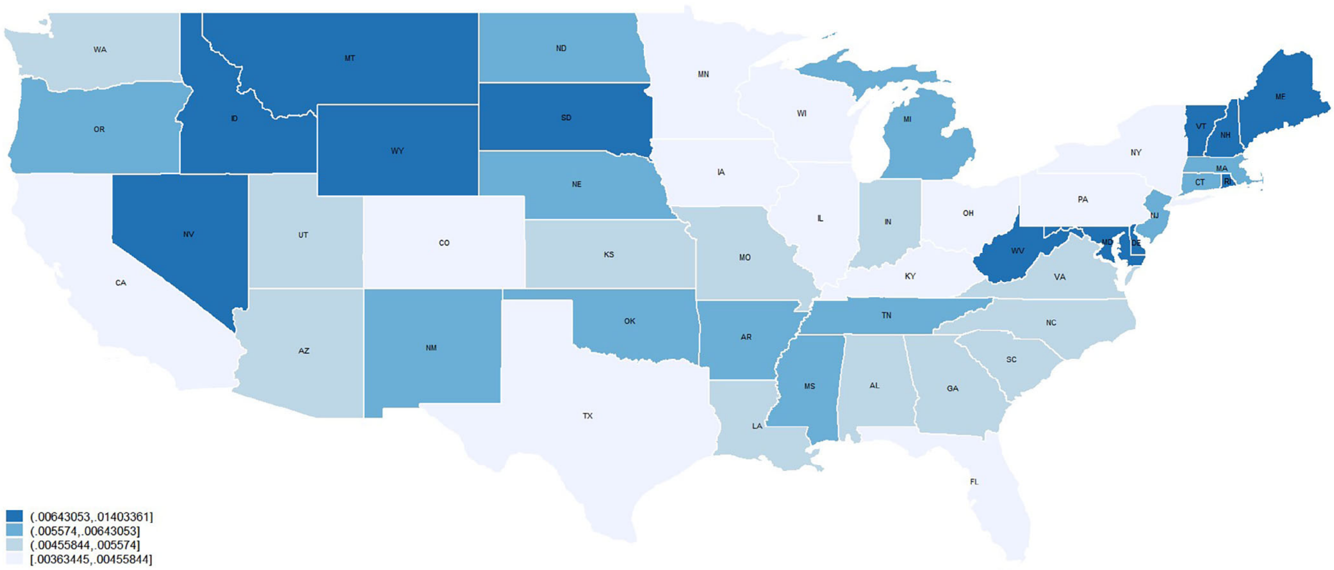

FIGURE 2 Labour reallocation index – 48 US States in 1990. [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 1 presents the graphs of the unemployment rate and the reallocation measure for the US at the regional (state) level. We can observe a significant level of heterogeneity in the US labour market (both in terms of the unemployment rate as well as the reallocation index). Figures 2 and 3 provide a map of the 48 US states

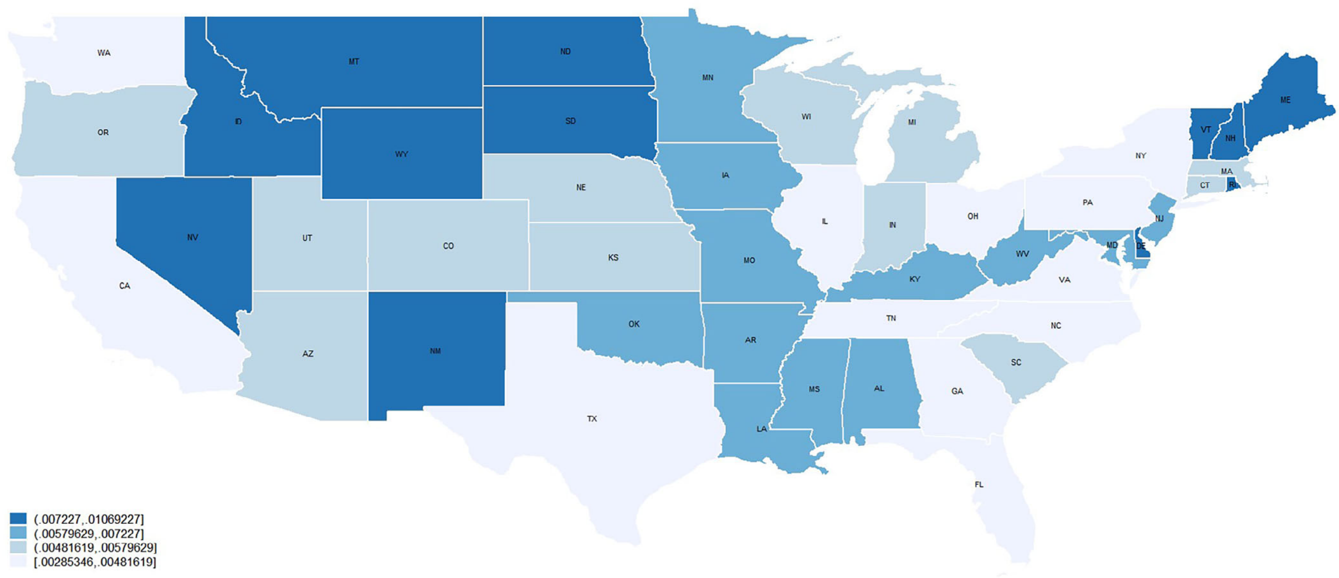

FIGURE 3 Labour reallocation index – 48 US States in 2016. [Colour figure can be viewed at wileyonlinelibrary.com]

with the different levels of labour reallocation as these captured by the state-level Lilien index (σ^9). Figure 2 provides the picture at the beginning of the sample (in 1990) and Figure 3 at the end (in 2016). This observed heterogeneity will be exploited using the quantile panel setting of Equation (1).

We investigate the heterogeneous effects of labour reallocation at different points of the distribution of US state unemployment by looking how the parameter $\beta^{(\tau)}$ changes as we move across quantiles. To do this, a panel quantile regression model is used (see Equation (1)) that relaxes the symmetry assumption (e.g., by employing the estimates of $\beta^{(\tau)}$ for a range of $\tau = 0.05$, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95). The panel specification of Equation (1) includes state fixed effects (μ_i). The estimation of a quantile model in a panel setting with fixed effects is not trivial, since the non-linearity for the conditional quantiles implies that the standard demeaning techniques are not feasible.

There are various ways proposed in the literature for estimating the quantile panel model with fixed effects (Canay, 2011; Koenker, 2004; Machado & Santos Silva, 2019; Powell, 2022; among others). We follow the approach of Canay (2011) to estimate the panel quantile regression model with the fixed effects.[9] The two-step method of Canay (2011) uses a simple transformation of the data to eliminate the fixed effects, as $T \rightarrow \infty$, under the assumption that these state fixed effects are location shift variables (i.e., they affect all quantiles in the same way). In the first step, the standard panel FE model at the conditional mean is estimated, and then the estimated parameters are used to obtain the individual fixed effect ($\widehat{\mu}_i$). In the second step, this component is subtracted from the dependent variable ($\widehat{U}_{i,t} = U_{i,t} - \widehat{\mu}_i$) and the estimation proceeds using the standard QR method.[10] Furthermore, we follow the approach of Parente and Santos Silva (2016) and employ clustered robust standard errors at the state level for inference.[11] In addition, and for the purposes of robustness of our findings, we implement two, recently proposed, alternative estimation methods for quantile panel data; the QR method for panel data with fixed effects of Machado and Santos Silva (2019) and the QR framework for panel data with nonadditive fixed effects of Powell (2022).

4 | EMPIRICAL RESULTS

We present the results of a reduced form of Equation (1) (including the state personal income growth as the only control) for the 48 US states panel over the period 1991M02-2016M12 in Table 2. Column 1 in Table 2 provides the estimates of the benchmark dynamic FE-LR panel model, while columns 2–12 present those of the dynamic panel QR estimation based on the approach of Canay (2011). The results from the FE-LR model show the persistence of unemployment (with a coefficient of lagged unemployment close to unity – 0.994) and that labour reallocation is a significant contributor to unemployment in the US states, with a coefficient for sigma slightly higher than unity (1.1), confirming the previous findings of Bakas et al. (2017).

Moving to the quantile panel model (columns 2–12 in Table 2), we observe a strong and highly significant

TABLE 2 Fixed effects and quantile panel regressions – Canay (2011) estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	0.994***	1.005***	1.012***	1.010***	0.990***	0.991***	0.995***	0.996***	0.995***	0.986***	0.983***	0.982***
	(1854.81)	(1040.81)	(1358.44)	(1031.29)	(475.96)	(1377.72)	(1652.38)	(1903.71)	(1305.38)	(699.12)	(890.93)	(647.37)
Sigma	1.100***	0.154	0.223***	0.419***	0.836***	0.520***	0.520***	0.684***	1.608***	1.871***	2.421***	3.243***
	(6.42)	(0.71)	(5.99)	(5.81)	(4.37)	(6.21)	(7.30)	(7.19)	(6.79)	(6.85)	(6.83)	(9.93)
ΔlnPI	−1.406***	−0.270**	−0.217***	−0.351***	−1.042***	−0.680***	−0.518***	−0.585***	−1.232***	−2.028***	−2.126***	−2.245***
	(−10.74)	(−2.14)	(−5.69)	(−7.14)	(−7.97)	(−5.77)	(−5.63)	(−5.01)	(−5.74)	(−14.49)	(−12.65)	(−18.18)
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323	323
Pseudo R^2	0.993	0.995	0.995	0.995	0.996	0.996	0.995	0.996	0.996	0.996	0.995	0.995

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). FE denotes the Fixed Effects method. Columns 2–12 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

TABLE 3 Fixed effects and quantile panel regressions – Canay (2011) estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	0.997***	1.008***	1.010***	1.010***	0.999***	0.992***	0.994***	0.996***	0.996***	0.993***	0.986***	0.985***
	(1902.81)	(924.08)	(468.46)	(1022.69)	(546.96)	(1857.56)	(1728.88)	(1905.14)	(1807.65)	(827.75)	(1193.64)	(777.71)
Sigma	0.765***	0.024	0.097	0.285***	0.584***	0.540***	0.399***	0.454***	0.851***	1.413***	1.416***	2.027***
	(5.33)	(0.12)	(0.79)	(4.24)	(5.23)	(5.18)	(6.35)	(6.13)	(9.05)	(9.79)	(7.22)	(7.44)
$\Delta lnPI$	−1.394***	−0.357***	−0.441***	−0.482***	−1.122***	−1.047***	−0.874***	−0.844***	−1.116***	−1.588***	−2.052***	−2.240***
	(−11.29)	(−3.22)	(−4.50)	(−7.18)	(−13.70)	(−9.20)	(−7.63)	(−5.90)	(−6.54)	(−10.48)	(−18.42)	(−15.40)
ΔFR	−0.026***	−0.022***	−0.020***	−0.025***	−0.027***	−0.022***	−0.019***	−0.020***	−0.025***	−0.031***	−0.027***	−0.023***
	(−21.24)	(−6.44)	(−6.92)	(−16.76)	(−21.17)	(−13.45)	(−12.57)	(−11.82)	(−17.76)	(−17.98)	(−12.15)	(−11.85)
HFR	0.035***	0.020***	0.021***	0.030***	0.029***	0.028***	0.035***	0.042***	0.048***	0.041***	0.040***	0.047***
	(16.79)	(8.20)	(8.17)	(14.01)	(9.76)	(14.24)	(19.73)	(19.20)	(24.29)	(12.96)	(11.80)	(10.38)
ΔlnG	0.798***	0.481***	0.367***	0.396***	0.867***	0.703***	0.487***	0.459***	0.637***	0.870***	0.928***	0.898***
	(13.70)	(4.56)	(3.36)	(8.76)	(16.79)	(12.40)	(8.96)	(8.10)	(13.31)	(21.22)	(18.17)	(8.03)
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323	323
Pseudo R^2	0.994	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). FE denotes the Fixed Effects method. Columns 2–12 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

persistence of unemployment for all quantiles. The coefficient of lagged unemployment is found higher for relatively low levels of unemployment but decreases for the upper part of the conditional distribution of u. The impact of state-specific personal income is negative and significant in all quantiles and is increasing for higher levels of unemployment. In other words, the higher the unemployment rate the larger the negative effect of $\Delta lnPI$ on u. The impact of the Lilien's dispersion index (*sigma*) on the unemployment rate is positive and becomes larger and more significant for the higher quantiles. The values of the sigma coefficients range from 0.15 (0.05 quantile) to 3.24 (0.95 quantile). As one moves above quantile 0.7, the estimated coefficients of QR surpass the FE one (1.1. for FE and 1.6, 1.8 2.4 and 3.2 for the last 4 quantiles). The results from Table 2 reveal that labour reallocation affects more the unemployment rate when its value is relatively high. This stylized feature would confirm the impact of labour reallocation is larger and increases for relatively higher levels of unemployment.

Having established a significant, positive, and asymmetric effect of reallocation for unemployment, we explore the robustness of the (u−σ) relationship when we control for additional, state-specific and common to all states, factors. These results are presented in Table 3. They reveal the persistent nature of US unemployment. The lagged unemployment coefficient is close to unity and strongly significant for all quantiles. The estimated value of the sigma coefficient in the FE-LR model is 0.76 (which is very close to the estimate in Bakas et al., 2017). The results of the QR panel model bear out the relevant features of the sectoral shifts hypothesis. There is a negligible and statistically insignificant reallocation impact (with a coefficient very close to zero – 0.024 for the 0.05 quantile) for (relative) low values of the unemployment rate. However, at higher unemployment levels the reallocation effect is strong and highly significant (with a coefficient of 2.03 for the 0.95 quantile).

As far as the control variables in the specification of Equation (1) (Table 3), we observe a negative and significant coefficient for the growth of state personal income ($\Delta lnPI$) with its magnitude to becoming more negative as the move higher quantiles of the conditional distribution for the unemployment rate. In other words, the higher is unemployment the more negative is the effect of the growth of state personal income. The coefficient of the changes in federal fund rates (ΔFR) is negative, significant without significant changes across the conditional distribution. The effect of *HFR* is positive and significant with an upward trend: the higher the unemployment the more positive is the effect of the variability in the federal funds rate. Significant, positive, and upward sloping is the coefficient of the changes in the local government

TABLE 4 Quantile panel regressions – Machado and Santos Silva (2019) estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	0.05	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	1.011***	1.008***	1.005***	1.002***	0.998***	0.996***	0.995***	0.993***	0.990***	0.985***	0.981***
	(735.78)	(894.16)	(1119.97)	(1319.48)	(1483.02)	(1475.68)	(1373.57)	(1224.55)	(970.80)	(718.93)	(577.85)
Sigma	−0.421**	−0.165	0.112	0.333***	0.614***	0.790***	0.932***	1.084***	1.352***	1.741***	2.063***
	(−2.10)	(−1.00)	(0.86)	(3.03)	(6.33)	(8.03)	(8.83)	(9.18)	(9.13)	(8.71)	(8.35)
$\Delta lnPI$	−0.518***	−0.708***	−0.912***	−1.075***	−1.283***	−1.412***	−1.518***	−1.630***	−1.827***	−2.115***	−2.353***
	(−4.92)	(−8.17)	(−13.24)	(−18.50)	(−24.97)	(−27.26)	(−27.28)	(−26.18)	(−23.39)	(−20.10)	(−18.06)
Include additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^{9}). Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Machado and Santos Silva (2019). *t-statistic* in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

TABLE 5 Quantile panel regressions – Powell (2022) estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	0.05	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	1.007***	1.007***	1.005***	0.994***	0.989***	0.990***	0.989***	0.990***	0.992***	0.971***	0.976***
	(317.77)	(364.47)	(304.79)	(149.69)	(236.81)	(236.35)	(288.16)	(260.63)	(407.13)	(126.31)	(185.65)
Sigma	−0.215*	−0.063	0.093	0.460*	0.393***	0.212**	0.199***	0.719***	1.322***	1.222***	1.879***
	(−1.77)	(−0.93)	(1.53)	(1.92)	(2.67)	(2.15)	(2.80)	(2.85)	(4.04)	(4.24)	(5.45)
ΔlnPI	−0.344***	−0.348***	−0.327***	−0.960***	−1.019***	−0.643**	−0.590***	−0.941***	−1.085***	−1.740***	−1.150***
	(−2.60)	(−3.28)	(−3.19)	(−2.85)	(−3.86)	(−2.55)	(−4.39)	(−2.71)	(−4.65)	(−4.73)	(−7.93)
Include additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Powell (2022). *T-statistic* in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

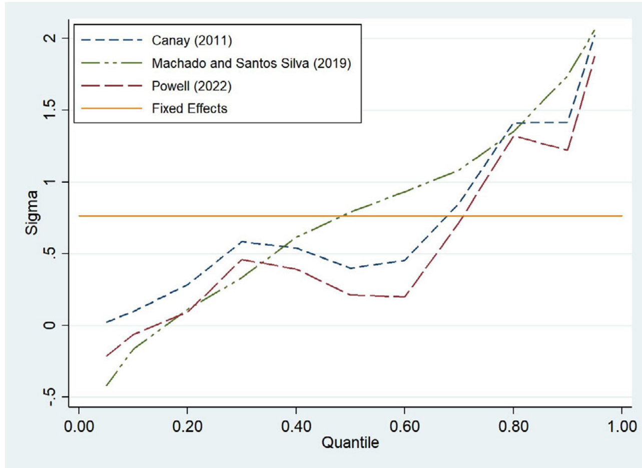

FIGURE 4 Fixed effects and alternative quantile panel estimators. [Colour figure can be viewed at wileyonlinelibrary.com]

expenditure (ΔlnG). The magnitude and the significance of the control variables remain the same in the robustness regressions that are presented in the next section.

5 | ROBUSTNESS ANALYSIS

We carry out robustness checks in six dimensions. First, we explore the robustness of our results on alternative estimation methods (Tables 4 and 5). We follow the estimation frameworks of Machado and Santos Silva (2019) and Powell (2022) as alternative approaches to Canay (2011). In both cases, we can observe similar outcomes to those of Table 3. The impact of reallocation is stronger as we move from lower to higher levels of unemployment. For comparison purposes, Figure 4 depicts the coefficients per quantile for the three alternative methods (Canay, 2011; Machado & Santos Silva, 2019; Powell, 2022) against the FE estimator. The FE estimate of the sigma coefficient corresponds to the median QR response ($\tau = 0.5$) based on the Machado and Santos Silva (2019) model, while it is found to be close to the median estimates based on the other two methods.

Tables 6 and 7 present our robustness findings for different measures of unemployment. Table 6 reports the evidence emerging when the aggregate US rate of unemployment, instead of the state unemployment rate, appears as the dependent variable in Equation (1). Table 7 provides the estimates when the dependent variable is replaced by the NEI index (the HKL non-employment index). Our main findings are unaffected by these changes. These results reaffirm the previous findings of Mills et al. (1995). The evidence from Table 7 also reveals that the aggregate impact of labour reallocation is weaker when we use the NEI measure instead of the

TABLE 6 Fixed effects and quantile panel regressions – US aggregate Un. rate.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	0.999***	1.013***	1.025***	1.007***	1.013***	1.000***	0.998***	0.999***	0.991***	0.983***	0.985***	0.974***
	(2201.52)	(2067.04)	(3728.89)	(3946.43)	(3096.09)	(1557.29)	(2462.26)	(2552.79)	(1758.16)	(2135.03)	(931.37)	(994.89)
Sigma	0.817***	−0.064	0.127	0.447***	0.481***	0.945***	0.489***	0.619***	1.101***	0.949***	1.929***	1.706***
	(8.96)	(−0.69)	(1.33)	(6.28)	(7.09)	(6.76)	(9.02)	(8.64)	(12.29)	(8.75)	(12.81)	(11.57)
ΔlnPI	−1.140***	−0.167*	−0.049	−0.436***	−0.424***	−1.090***	−0.874***	−0.843***	−1.232***	−1.315***	−1.606***	−1.637***
	(−10.82)	(−1.79)	(−1.21)	(−4.69)	(−6.09)	(−7.65)	(−7.90)	(−7.38)	(−11.32)	(−11.66)	(−13.21)	(−16.44)
ΔFR	−0.020***	−0.015***	−0.011***	−0.005***	−0.013***	−0.029***	−0.019***	−0.022***	−0.043***	−0.037***	−0.026***	−0.028***
	(−27.83)	(−27.05)	(−58.02)	(−10.38)	(−21.61)	(−17.32)	(−21.64)	(−31.79)	(−31.76)	(−35.04)	(−17.97)	(−12.21)
HFR	0.043***	0.046***	0.061***	0.053***	0.054***	0.039***	0.036***	0.047***	0.022***	0.020***	0.035***	0.045***
	(84.30)	(24.81)	(98.96)	(73.21)	(90.10)	(51.68)	(59.40)	(42.51)	(14.04)	(14.55)	(17.34)	(11.63)
ΔlnG	0.786***	0.157**	−0.021	0.246***	0.108***	0.233***	0.304***	0.561***	1.187***	1.092***	1.381***	1.372***
	(30.63)	(2.28)	(−0.75)	(12.40)	(5.12)	(6.83)	(8.81)	(18.65)	(30.36)	(39.46)	(29.56)	(26.28)
Obs	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200
N	48	48	48	48	48	48	48	48	48	48	48	48
T	275	275	275	275	275	275	275	275	275	275	275	275
Pseudo R^2	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990

Note: The dependent variable is the aggregate US unemployment rate (U) in logistic form. *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). FE denotes the Fixed Effects method. Columns 2–12 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE 7 Fixed effects and quantile panel regressions – US non-employment index.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
NEI_{Lagged}	0.994***	1.000***	0.995***	0.990***	0.991***	0.995***	0.999***	1.002***	1.000***	1.003***	0.996***	0.980***
	(1844.92)	(1332.44)	(1792.28)	(2313.24)	(2842.48)	(1936.34)	(1795.82)	(1335.54)	(1286.86)	(1262.79)	(968.87)	(954.58)
Sigma	0.321***	0.364***	0.191***	0.115***	0.147***	0.124***	0.213***	0.286***	0.244***	0.444***	0.423***	0.665***
	(7.95)	(12.04)	(6.54)	(4.05)	(6.45)	(5.98)	(7.22)	(10.21)	(6.61)	(7.45)	(6.77)	(8.44)
$\Delta lnPI$	−0.547***	0.079***	−0.070***	−0.264***	−0.221***	−0.347***	−0.429***	−0.536***	−0.644***	−0.722***	−0.788***	−0.861***
	(−12.01)	(2.77)	(−2.96)	(−10.05)	(−7.13)	(−8.38)	(−9.68)	(−10.11)	(−12.77)	(−16.53)	(−14.75)	(−17.07)
ΔFR	−0.013***	−0.015***	−0.012***	−0.015***	−0.016***	−0.015***	−0.016***	−0.013***	−0.013***	−0.014***	−0.010***	−0.001
	(−40.66)	(−77.28)	(−73.05)	(−56.96)	(−87.75)	(−59.31)	(−47.05)	(−26.33)	(−19.40)	(−21.72)	(−16.93)	(−1.53)
HFR	0.019***	0.024***	0.022***	0.015***	0.013***	0.015***	0.014***	0.017***	0.017***	0.015***	0.024***	0.035***
	(81.43)	(180.63)	(175.86)	(52.29)	(57.27)	(38.31)	(32.36)	(38.12)	(40.65)	(16.01)	(7.45)	(31.17)
ΔlnG	0.207***	−0.036	0.147***	0.086***	0.042***	0.093***	0.181***	0.273***	0.268***	0.383***	0.365***	0.355***
	(17.77)	(−1.51)	(14.31)	(9.04)	(4.09)	(10.23)	(16.29)	(28.81)	(17.83)	(18.91)	(13.60)	(10.22)
Obs	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200	13,200
N	48	48	48	48	48	48	48	48	48	48	48	48
T	275	275	275	275	275	275	275	275	275	275	275	275
Pseudo R^2	0.990	0.989	0.989	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.989

Note: The dependent variable is the US non-employment index (*NEI*) in logistic form. *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). FE denotes the Fixed Effects method. Columns 2–12 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE 8 Quantile panel regressions – alternative measures of sigma.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	0.05	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
Sigma (σ^{13})	−0.114	0.014	0.144**	0.421***	0.438***	0.337***	0.351***	0.690***	1.062***	1.134***	1.761***
	(−0.51)	(0.27)	(1.98)	(2.99)	(3.71)	(4.83)	(6.48)	(7.33)	(7.19)	(6.12)	(4.92)
Sigma (σ^{10})	0.065	0.078	0.271***	0.570***	0.523***	0.388***	0.418***	0.785***	1.242***	1.280***	1.968***
	(0.43)	(0.96)	(4.35)	(6.22)	(5.82)	(6.07)	(5.79)	(6.32)	(6.81)	(7.39)	(5.73)
Sigma (σ^{9})	0.024	0.097	0.285***	0.584***	0.540***	0.399***	0.454***	0.851***	1.413***	1.416***	2.027***
	(0.12)	(0.79)	(4.24)	(5.23)	(5.18)	(6.35)	(6.13)	(9.05)	(9.79)	(7.22)	(7.44)

Note: *Sigma* ($\sigma^9/\sigma^{10}/\sigma^{13}$) is the labour reallocation index for the 9/10/13 sectors of the US economy, respectively. Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016) and by employing the specification used in Table 3. The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *T-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

unemployment rate. This comparatively smaller effect might suggest that reallocation shocks have a relatively larger effect on short term unemployment (i.e., on workers who have been actively looking for work over the previous month) than on discouraged workers.

We also explore the robustness over alternative reallocation indexes that are constructed with a different degree of sectoral disaggregation. Table 8 presents the results for three dispersion proxies corresponding to three different levels of sectoral decomposition (9, 10 and 13 sectors respectively). The sigma coefficient remains positive and significant under the alternative sectoral disaggregation measures, confirming similar findings with Bakas et al. (2017). It should be noted that the magnitude of the coefficient of labour reallocation decreases as the sectoral disaggregation increases, thus bearing out results in Parker (1992) and Bakas et al. (2017). Finally, we can observe that the effect of reallocation over the alternative quantiles is unaffected by the measure of turbulence. The effect on unemployment is small and insignificant in low quantiles while it is appreciably larger and more significant in the higher quantiles.

Fourth, we also check the effect of changes in the pace of intersectoral reallocation to assess whether pace acceleration would also reflect the asymmetric nature of the shifts. We estimate Equation (1) where, instead of the level of the reallocation measure (*sigma*), we use the first differences of Lilien's sigma index (*Δsigma*) which measures the change in the pace of labour reallocation (Table 9). We observe, from Table 9, that the impact of labour reallocation is very close to zero and insignificant for the lower and median quantiles and becomes stronger and more significant only when we move to the high unemployment quantiles ($\tau > 0.8$). The latter implies that reallocation and the speed of reallocation increases when unemployment is relatively high.

Fifth, we follow the work of Bakas et al. (2017) and explore the robustness of our results to the alternative transformation of the unemployment rate (logistic vs. logarithmic form). In this way, we re-estimate the specification used in Table 3 by replacing the logistic transformation of the unemployment rate with the logarithmic form ($u_{i,t} = ln(U_{i,t})$, with $U_{i,t}$ is the unemployment rate in decimal). Table 10 presents the results of this alternative specification and shows that our main findings are unaffected by the transformation of the dependent variable. These results reinforce the analogous evidence in Bakas et al. (2017).

Finally, we check the robustness of our results to the inclusion of additional controls, like the exchange rate, economic policy uncertainty, oil prices, house prices, stock market returns and stock market volatility (Tables A1–A6 in the Appendix A). Our results, from the extended versions of Equation (1), as presented in Tables A1–A6, are found to be very robust to the alternative control variables and specifications used. The impact of labour reallocation is mostly positive and becomes stronger and more significant as we move to higher unemployment quantiles. It is worth mentioning the significant effect of house price returns (*ΔlnHPI*) (negative), effective exchange rate growth (*ΔlnEER*) (negative), policy uncertainty (*lnEPU*) (positive), stock market returns (*ΔlnSP*) (negative) and stock market volatility (*SPRV*) (positive) as seen in Table A6. For comparison purposes, Figure 5 shows the coefficients per quantile for sigma based on three alternative specifications used in the analysis – the benchmark specification (Table 3), the specification with some additional controls (Table A5) and the specification with all controls (Table A6). As can be observed from Figure 5 the main findings are unaffected by the use of alternative specifications and are robust to the inclusion of additional controls.

TABLE 9 Fixed effects and quantile panel regressions – first differences of Sigma.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	0.05	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	1.008***	1.010***	1.010***	0.999***	0.992***	0.995***	0.996***	0.996***	0.992***	0.985***	0.984***
	(997.58)	(474.42)	(915.38)	(534.60)	(1872.07)	(1672.16)	(1865.54)	(1643.27)	(860.99)	(1072.19)	(980.69)
$\Delta Sigma$	0.099	−0.028	−0.024	0.024	0.053	0.005	−0.004	0.052	0.137*	0.180***	0.274***
	(0.74)	(−0.59)	(−0.70)	(0.45)	(1.24)	(0.22)	(−0.15)	(1.24)	(1.96)	(2.99)	(3.61)
$\Delta lnPI$	−0.370***	−0.435***	−0.443***	−1.090***	−1.034***	−0.794***	−0.769***	−1.080***	−1.683***	−2.160***	−2.352***
	(−3.25)	(−4.43)	(−6.03)	(−12.37)	(−8.45)	(−6.74)	(−5.33)	(−5.84)	(−10.67)	(−19.66)	(−14.98)
ΔFR	−0.021***	−0.020***	−0.024***	−0.028***	−0.023***	−0.020***	−0.020***	−0.026***	−0.033***	−0.027***	−0.024***
	(−6.55)	(−7.41)	(−13.28)	(−19.27)	(−12.57)	(−11.20)	(−11.98)	(−16.51)	(−21.37)	(−16.51)	(−12.23)
HFR	0.021***	0.021***	0.031***	0.031***	0.029***	0.035***	0.045***	0.050***	0.042***	0.043***	0.055***
	(7.70)	(9.47)	(16.26)	(13.67)	(14.79)	(20.60)	(15.91)	(19.20)	(16.83)	(13.73)	(9.75)
ΔlnG	0.478***	0.377***	0.380***	0.870***	0.690***	0.468***	0.427***	0.626***	0.886***	0.914***	0.956***
	(3.85)	(3.35)	(7.40)	(15.59)	(11.77)	(8.55)	(6.95)	(11.04)	(18.86)	(15.29)	(11.46)
Obs	15,456	15,456	15,456	15,456	15,456	15,456	15,456	15,456	15,456	15,456	15,456
N	48	48	48	48	48	48	48	48	48	48	48
T	322	322	322	322	322	322	322	322	322	322	322
Pseudo R^2	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). $\Delta Sigma$ is the first differences of the labour reallocation index for the 9 main sectors of the US economy (σ^9). Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE 10 Fixed effects and quantile panel regressions – logarithmic form of Un. rate.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	0.996***	1.009***	1.011***	1.011***	1.000***	0.993***	0.994***	0.996***	0.996***	0.992***	0.985***	0.983***
	(1889.55)	(955.14)	(512.45)	(991.70)	(544.17)	(1891.33)	(1724.72)	(1962.77)	(1852.71)	(743.08)	(1129.22)	(757.27)
Sigma	0.706***	0.025	0.084	0.261***	0.538***	0.504***	0.374***	0.421***	0.795***	1.312***	1.296***	1.872***
	(5.34)	(0.12)	(0.65)	(4.06)	(5.02)	(5.21)	(6.21)	(6.00)	(8.33)	(9.72)	(7.18)	(7.63)
$\Delta lnPI$	−1.307***	−0.343***	−0.412***	−0.463***	−1.066***	−0.989***	−0.814***	−0.791***	−1.040***	−1.476***	−1.943***	−2.114***
	(−11.37)	(−3.34)	(−4.84)	(−7.58)	(−14.10)	(−9.13)	(−7.48)	(−5.97)	(−6.74)	(−9.89)	(−18.33)	(−15.75)
ΔFR	−0.024***	−0.021***	−0.019***	−0.023***	−0.026***	−0.021***	−0.018***	−0.019***	−0.024***	−0.030***	−0.025***	−0.022***
	(−21.22)	(−6.24)	(−7.20)	(−16.45)	(−21.81)	(−13.21)	(−12.39)	(−12.75)	(−19.35)	(−19.28)	(−12.37)	(−11.95)
HFR	0.033***	0.019***	0.020***	0.029***	0.027***	0.027***	0.033***	0.040***	0.044***	0.039***	0.037***	0.044***
	(16.89)	(8.03)	(9.67)	(17.04)	(11.05)	(14.98)	(19.48)	(17.66)	(23.49)	(12.68)	(12.20)	(8.84)
ΔlnG	0.747***	0.465***	0.343***	0.375***	0.818***	0.656***	0.459***	0.429***	0.593***	0.813***	0.873***	0.856***
	(13.65)	(4.89)	(3.54)	(8.74)	(17.13)	(12.07)	(9.19)	(8.14)	(13.62)	(20.58)	(18.48)	(6.95)
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323	323
Pseudo R^2	0.994	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Note: The dependent variable is the US state level unemployment rate in logarithmic form (U^{ln}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). FE denotes the Fixed Effects method. Columns 2–12 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

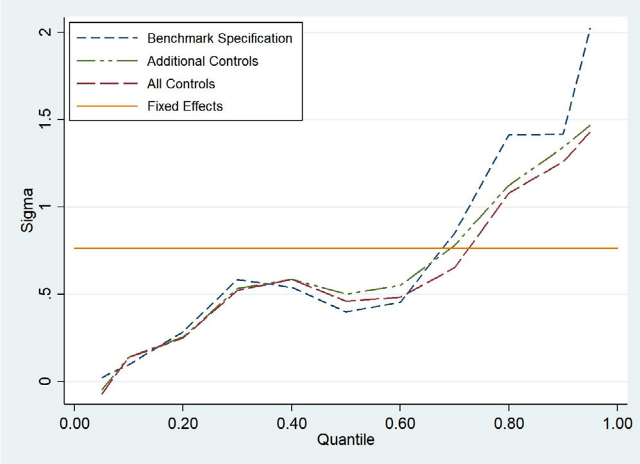

FIGURE 5 Fixed effects and alternative quantile panel specifications. [Colour figure can be viewed at wileyonlinelibrary.com]

6 | CONCLUSIONS

We examine the macroeconomic effects of labour reallocation using a monthly panel dataset for 48 US states spanning from 1990 to 2016. Most of the previous empirical approaches have focused on either time-series or panel data analyses assuming a linear framework and have focused on the average effect. We relax this restrictive assumption of symmetry and examine the relationship between labour reallocation and unemployment across the conditional distribution of the unemployment rate. We employed three recently developed panel quantile regression models by Canay (2011), Machado and Santos Silva (2019) and Powell (2022).

We substantiate the positive impact of the reallocation index on unemployment in the US. Our findings reveal a statistically significant and increasing in magnitude effect of labour reallocation on unemployment. The impact of Lilien's reallocation measure becomes significantly bigger as we move from the lower to the upper quantiles of the unemployment rate. Our results are robust to a battery of robustness checks, including alternative measures of reallocation and unemployment, several control variables, and alternative estimation methods.

Future lines of research can perform a deeper exploration of the endogeneity problem of labour reallocation by utilising an external shock in the economy, for example, the Covid-19 shock, or by using a difference–in–difference approach. Another direction of future research is to exploit further the multiple dimensions of labour reallocation through employing a micro-econometrics approach, using firm level data, and therefore by utilising a multidimensional panel dataset (firm/sector/state). We leave these suggestions as potential avenues for future research.

ACKNOWLEDGEMENTS

We would like to thank John Addison, David Andolfatto, Costas Azariadis, Richard Baillie, Alessandro Cigno, Steven Davis, Giovanni Gallipoli, Paolo Giordani, Guido Imbens, David Laidler, Anthony Lancaster, John Murray, Michael Parkin and Michael Plummer for their useful comments and suggestions on earlier versions of this work. Any remaining errors are the responsibility of the authors.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] Elsby et al. (2010), Estevão and Tsounta (2011), Davis et al. (2012), Diamond (2013) and Blanchard et al. (2014), Bauer and King (2018), Chodorow-Reich and Wieland (2020), Dieppe and Matsuoka (2021).

[2] Davis (1987) is an early attempt to study sectoral shifts asymmetries. It shows that even in a linear econometric specification, it is possible to draw (limited) inferences about asymmetric and other nonlinear effects of shocks on the unemployment rate. Davis shows evidence that the recent past pattern of labour reallocation matters for unemployment outcomes. When current and recent past sectoral shifts are in the same direction, the impact on current unemployment is greater.

[3] The dataset covers the period from January 1990 to December 2016 due to data availability of the state employment series from the US Bureau of Labour Statistics. Our analysis starts in February 1990 rather than January since we lose one observation for the calculation of the Lilien's employment dispersion measure ($\sigma_{i,t}$).

[4] Our empirical specification of a Lilien's reduced form unemployment equation builds on the work of Mills et al. (1995) and the recent panel extension of Bakas et al. (2017), and allows for a large set of (state-specific and common to all states) covariates to provide an in-depth test of the sectoral shifts hypothesis. See also Panagiotidis and Pelloni (2014), for a discussion of the reduced form specification of the quantile model.

[5] Following Bakas et al. (2017) we use the logistic form of the unemployment rate as the dependent variable, $U_{i,t} = ln(u_{i,t}/1\text{-}u_{i,t})$, where $u_{i,t}$ is the unemployment rate (in decimal form). According to Wallis (1987) the logistic transformation is preferred since unemployment rate is a variable that is bounded between 0 and 1. Replacing the logistic form with the logarithmic

form does not alter the outcome qualitatively. We provide evidence for this in the robustness section of the paper, while a full set of empirical results is available upon request.

[6] The sample for the analysis, in this case, is restricted to 1994:M01 to 2016:M12 due to the availability of the NEI index.

[7] Abraham and Katz (1986) point out the problem of 'observational equivalence' regarding the sensitivity of the employment dispersion index of Lilien (1982) to aggregate shocks. For robustness purposes, we have also implemented all estimations using a 'purged' measure of the Lilien's dispersion index, where we filter out aggregate effects from the sectoral dispersion proxy, following the approach used in Bakas et al. (2017). Replacing the unpurged Lilien's measure ($\sigma_{i,t}$) with the 'purged' version does not alter the results qualitatively, confirming a similar outcome with that of Bakas et al. (2017). These results are available upon request.

[8] Using this 10-industry decomposition, we compute our benchmark measure (*sigma* - σ^9) using the information on the 9 'super-sectors' of the economy (i.e., excluding the government sector), while we also compute a 13-sectors decomposition measure of labour reallocation (σ^{13}) by using all the available disaggregation in our dataset (including the government sector), and finally a 10-sectors decomposition measure including all 10 'super-sectors' of the economy (σ^{10}).

[9] The quantile panel estimator of Canay (2011) has been widely used in recent empirical studies (Besstremyannaya & Golovan, 2019). The advantage of Canay's (Canay, 2011) approach is that it provides a quantile panel estimator which is easy to implement and is based on a simple two-step approach to control for the individual fixed effects. In that way, this two-step approach has low computational cost, especially for large panel datasets like the one we employ here, and offers a simple way for the consistent estimation of individual effects.

[10] The panel QR approach, thus, accounts for these two important aspects (heterogeneity and non-linearity) of the sectoral shifts hypothesis. In addition, using the purging strategy of Abraham and Katz (1986) the QR panel approach can alleviate any potential endogeneity problem of labour reallocation. Other approaches have been suggested in the literature to address the endogeneity of reallocation (see, for example, Bakas et al., 2016, 2017 and Chodorow-Reich & Wieland, 2020, among others). Bakas et al. (2016, 2017) use a system GMM approach to tackle endogeneity, by employing lagged levels and differences of the endogenous variables as instruments, while Chodorow-Reich and Wieland (2020) use an instrumental variable framework, by exploring a Bartik-style measure of predicted reallocation as an instrument for actual reallocation.

[11] For robustness purposes, we have also implemented the estimation using bootstrapped standard errors. The main findings, using this alternative method to obtain the variance–covariance matrix for this estimator, remain unaltered. These results are available upon request.

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How to cite this article: Bakas, D., Panagiotidis, T., & Pelloni, G. (2023). Labour reallocation and unemployment fluctuations: A tale of two tails. *International Journal of Finance & Economics*, 1–25. https://doi.org/10.1002/ijfe.2845

APPENDIX A

In this Appendix, we present the tables with some additional robustness checks. More specifically, we have explored the robustness of our main results using extended specifications of Equation (1) with the inclusion of additional control variables, such as the exchange rate, economic policy uncertainty, oil prices, house prices, stock market returns and stock market volatility. The results are presented in Tables A1–A6 below.

TABLE A1 Quantile panel regressions – additional control variables (*Exchange Rate*).

	(1) 0.05	(2) 0.1	(3) 0.2	(4) 0.3	(5) 0.4	(6) 0.5	(7) 0.6	(8) 0.7	(9) 0.8	(10) 0.9	(11) 0.95
U_{Lagged}	1.007***	1.010***	1.009***	0.999***	0.993***	0.994***	0.996***	0.996***	0.992***	0.985***	0.984***
	(918.76)	(412.04)	(946.72)	(550.77)	(1661.00)	(1721.65)	(1886.01)	(1677.85)	(751.41)	(1208.71)	(766.08)
Sigma	−0.007	0.102	0.288***	0.559***	0.527***	0.407***	0.482***	0.847***	1.390***	1.399***	2.029***
	(−0.03)	(1.01)	(4.16)	(4.80)	(5.08)	(6.01)	(6.24)	(9.92)	(10.14)	(7.94)	(7.19)
ΔlnPI	−0.404***	−0.450***	−0.524***	−1.111***	−1.072***	−0.886***	−0.848***	−1.111***	−1.566***	−2.080***	−2.245***
	(−3.40)	(−3.99)	(−8.19)	(−11.62)	(−9.03)	(−7.46)	(−6.10)	(−6.60)	(−10.21)	(−19.06)	(−14.65)
ΔFR	−0.020***	−0.020***	−0.025***	−0.026***	−0.022***	−0.020***	−0.021***	−0.026***	−0.032***	−0.026***	−0.024***
	(−5.97)	(−6.58)	(−16.06)	(−16.47)	(−13.05)	(−11.90)	(−12.31)	(−19.59)	(−15.10)	(−12.10)	(−11.26)
HFR	0.019***	0.021***	0.030***	0.030***	0.028***	0.034***	0.042***	0.048***	0.043***	0.042***	0.046***
	(6.61)	(6.67)	(14.85)	(11.03)	(15.50)	(21.70)	(19.56)	(21.00)	(14.96)	(7.68)	(11.03)
ΔlnG	0.492***	0.352***	0.415***	0.838***	0.700***	0.489***	0.452***	0.635***	0.855***	0.900***	0.917***
	(4.37)	(3.15)	(8.60)	(16.27)	(11.79)	(8.67)	(7.90)	(13.37)	(20.23)	(20.04)	(7.29)
ΔlnEER	−0.069**	−0.025*	−0.036***	−0.097***	−0.050***	−0.018***	−0.026***	−0.064***	−0.086***	−0.042***	−0.016
	(−2.38)	(−1.91)	(−3.97)	(−6.25)	(−4.30)	(−2.77)	(−3.92)	(−8.29)	(−6.39)	(−2.95)	(−0.71)
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323
Pseudo R^2	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE A2 Quantile panel regressions – additional control variables (*Oil Prices*).

	(1) 0.05	(2) 0.1	(3) 0.2	(4) 0.3	(5) 0.4	(6) 0.5	(7) 0.6	(8) 0.7	(9) 0.8	(10) 0.9	(11) 0.95
U_{Lagged}	1.008***	1.010***	1.010***	0.999***	0.992***	0.994***	0.996***	0.996***	0.993***	0.986***	0.984***
	(914.58)	(467.65)	(1028.51)	(573.13)	(1689.60)	(1713.61)	(1906.53)	(1847.34)	(792.97)	(1219.91)	(738.92)
Sigma	−0.022	0.092	0.280***	0.577***	0.540***	0.398***	0.455***	0.846***	1.373***	1.378***	1.987***
	(−0.12)	(0.69)	(4.12)	(6.08)	(5.16)	(6.33)	(6.20)	(9.00)	(10.05)	(7.82)	(6.90)
ΔlnPI	−0.344***	−0.437***	−0.480***	−1.096***	−1.044***	−0.872***	−0.839***	−1.120***	−1.606***	−2.072***	−2.249***
	(−3.38)	(−4.44)	(−7.24)	(−12.66)	(−9.27)	(−7.52)	(−5.80)	(−6.58)	(−10.46)	(−18.31)	(−16.60)
ΔFR	−0.024***	−0.020***	−0.025***	−0.028***	−0.023***	−0.019***	−0.020***	−0.026***	−0.032***	−0.028***	−0.026***
	(−7.07)	(−6.98)	(−16.50)	(−24.06)	(−13.27)	(−12.12)	(−11.52)	(−17.87)	(−20.06)	(−15.58)	(−12.24)
HFR	0.020***	0.021***	0.030***	0.028***	0.029***	0.035***	0.042***	0.048***	0.042***	0.043***	0.051***
	(5.30)	(8.03)	(14.02)	(7.91)	(14.90)	(20.33)	(18.66)	(25.23)	(14.34)	(14.31)	(11.14)
ΔlnG	0.467***	0.367***	0.395***	0.831***	0.712***	0.486***	0.455***	0.633***	0.832***	0.877***	0.824***
	(4.55)	(3.36)	(8.84)	(15.16)	(12.01)	(9.00)	(7.96)	(14.03)	(17.92)	(19.35)	(6.96)
ΔlnOIL	0.013***	0.000	0.000	0.010***	0.006***	−0.000	−0.000	0.002	0.009***	0.011***	0.013***
	(3.26)	(0.26)	(0.10)	(3.00)	(2.69)	(−0.18)	(−0.38)	(1.03)	(3.29)	(4.13)	(3.69)
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323
Pseudo R^2	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE A3 Quantile panel regressions – additional control variables (*Economic Policy Uncertainty*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	0.05	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	1.004***	1.006***	1.003***	0.992***	0.986***	0.989***	0.990***	0.989***	0.984***	0.977***	0.974***
	(738.40)	(498.87)	(714.32)	(612.73)	(1472.57)	(1288.68)	(1499.13)	(1378.20)	(738.60)	(796.89)	(567.57)
Sigma	0.006	0.140	0.293***	0.577***	0.596***	0.444***	0.533***	0.790***	1.258***	1.358***	1.759***
	(0.03)	(1.09)	(4.70)	(7.10)	(6.21)	(5.68)	(7.77)	(7.47)	(8.74)	(6.19)	(6.59)
$\Delta lnPI$	−0.404***	−0.472***	−0.526***	−1.044***	−1.066***	−0.888***	−0.856***	−1.119***	−1.583***	−1.991***	−2.078***
	(−3.42)	(−5.10)	(−8.62)	(−14.58)	(−9.47)	(−7.72)	(−6.55)	(−8.12)	(−12.29)	(−16.32)	(−13.33)
ΔFR	−0.022***	−0.020***	−0.024***	−0.021***	−0.020***	−0.019***	−0.019***	−0.021***	−0.022***	−0.018***	−0.016***
	(−7.06)	(−8.50)	(−15.18)	(−13.05)	(−13.28)	(−11.90)	(−15.46)	(−14.78)	(−16.72)	(−7.88)	(−6.61)
HFR	0.019***	0.022***	0.029***	0.027***	0.027***	0.033***	0.039***	0.044***	0.041***	0.041***	0.045***
	(7.90)	(8.16)	(14.32)	(10.83)	(12.65)	(17.67)	(16.98)	(16.87)	(18.77)	(13.53)	(12.96)
ΔlnG	0.525***	0.373***	0.522***	0.918***	0.838***	0.571***	0.580***	0.742***	0.898***	0.994***	0.970***
	(4.55)	(4.05)	(9.42)	(18.51)	(12.06)	(9.15)	(11.73)	(19.90)	(19.91)	(18.02)	(10.08)
lnEPU	0.006***	0.004***	0.007***	0.012***	0.010***	0.008***	0.008***	0.011***	0.016***	0.016***	0.019***
	(3.03)	(3.06)	(8.79)	(14.10)	(8.35)	(8.03)	(12.56)	(14.77)	(14.85)	(9.12)	(9.80)
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323
Pseudo R^2	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE A4 Quantile panel regressions – additional control variables (*House Prices*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	0.05	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	1.005***	1.007***	1.006***	0.994***	0.990***	0.991***	0.993***	0.992***	0.989***	0.982***	0.979***
	(892.04)	(520.73)	(730.50)	(595.14)	(1593.06)	(1966.92)	(1745.04)	(1199.26)	(768.00)	(812.97)	(860.55)
Sigma	−0.027	0.109	0.286***	0.555***	0.515***	0.461***	0.507***	0.898***	1.266***	1.391***	1.744***
	(−0.12)	(1.20)	(3.31)	(4.57)	(6.40)	(5.88)	(6.65)	(8.15)	(8.13)	(6.22)	(10.13)
$\Delta lnPI$	−0.470***	−0.550***	−0.566***	−1.091***	−1.055***	−0.954***	−0.956***	−1.157***	−1.472***	−1.850***	−1.948***
	(−3.79)	(−5.94)	(−7.77)	(−11.87)	(−9.49)	(−8.85)	(−6.65)	(−7.03)	(−10.72)	(−15.78)	(−16.92)
ΔFR	−0.020***	−0.018***	−0.025***	−0.024***	−0.020***	−0.018***	−0.020***	−0.023***	−0.026***	−0.023***	−0.022***
	(−8.03)	(−8.15)	(−14.24)	(−17.62)	(−15.33)	(−11.76)	(−16.03)	(−15.62)	(−20.99)	(−12.87)	(−13.64)
HFR	0.018***	0.022***	0.028***	0.025***	0.028***	0.034***	0.040***	0.044***	0.040***	0.037***	0.041***
	(7.95)	(8.76)	(13.81)	(8.36)	(15.18)	(15.51)	(19.79)	(16.59)	(10.97)	(13.16)	(11.36)
ΔlnG	0.425***	0.374***	0.424***	0.784***	0.681***	0.522***	0.515***	0.679***	0.822***	0.834***	0.888***
	(3.75)	(4.44)	(7.84)	(13.90)	(12.41)	(10.07)	(10.39)	(14.39)	(18.55)	(15.72)	(12.01)
$\Delta lnHPI$	−0.442***	−0.386***	−0.383***	−0.640***	−0.654***	−0.540***	−0.525***	−0.627***	−0.817***	−0.882***	−1.041***
	(−4.50)	(−4.76)	(−7.70)	(−10.39)	(−9.80)	(−7.92)	(−9.06)	(−9.16)	(−11.91)	(−10.39)	(−10.38)
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323
Pseudo R^2	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE A5 Quantile panel regressions – additional control variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	0.05	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	1.002***	1.002***	0.999***	0.989***	0.984***	0.985***	0.986***	0.985***	0.981***	0.973***	0.970***
	(643.44)	(484.73)	(563.13)	(593.37)	(1136.01)	(1489.53)	(1440.95)	(1090.03)	(755.40)	(654.54)	(580.94)
Sigma	−0.047	0.140	0.255***	0.533***	0.587***	0.501***	0.551***	0.781***	1.124***	1.342***	1.468***
	(−0.25)	(1.64)	(3.17)	(6.98)	(6.28)	(6.54)	(7.13)	(7.17)	(7.88)	(9.10)	(7.87)
ΔlnPI	−0.505***	−0.589***	−0.614***	−1.063***	−1.075***	−0.947***	−0.902***	−1.124***	−1.430***	−1.726***	−1.848***
	(−3.91)	(−5.49)	(−8.73)	(−14.89)	(−10.11)	(−8.06)	(−7.36)	(−8.00)	(−13.26)	(−17.73)	(−14.79)
ΔFR	−0.017***	−0.017***	−0.022***	−0.019***	−0.017***	−0.018***	−0.018***	−0.019***	−0.020***	−0.018***	−0.015***
	(−6.38)	(−7.19)	(−13.55)	(−12.98)	(−13.28)	(−14.06)	(−16.22)	(−16.14)	(−14.80)	(−9.09)	(−6.76)
HFR	0.016***	0.022***	0.026***	0.024***	0.027***	0.033***	0.040***	0.043***	0.042***	0.041***	0.044***
	(4.46)	(9.51)	(11.05)	(11.02)	(11.54)	(13.94)	(21.15)	(21.29)	(17.20)	(10.99)	(10.66)
ΔlnG	0.485***	0.413***	0.577***	0.888***	0.795***	0.585***	0.573***	0.710***	0.853***	0.883***	0.882***
	(4.68)	(4.96)	(9.04)	(16.41)	(12.84)	(10.81)	(14.01)	(19.93)	(20.65)	(14.95)	(12.98)
ΔlnHPI	−0.470***	−0.440***	−0.400***	−0.570***	−0.633***	−0.600***	−0.533***	−0.619***	−0.727***	−0.831***	−0.928***
	(−5.02)	(−5.18)	(−8.15)	(−8.27)	(−9.55)	(−10.13)	(−8.93)	(−8.99)	(−11.61)	(−9.33)	(−9.53)
ΔlnEER	−0.075***	−0.041**	−0.046***	−0.061***	−0.029**	−0.021***	−0.031***	−0.050***	−0.058***	−0.031*	0.002
	(−2.71)	(−2.03)	(−4.61)	(−4.36)	(−2.57)	(−3.34)	(−4.35)	(−6.09)	(−5.69)	(−1.87)	(0.12)
ΔlnOIL	0.003	−0.002	−0.002	0.001	0.007***	0.003*	0.002	0.000	0.003	0.009***	0.009***
	(0.76)	(−0.73)	(−1.04)	(0.57)	(3.21)	(1.91)	(1.03)	(0.06)	(1.52)	(2.89)	(3.08)
lnEPU	0.004**	0.005***	0.007***	0.011***	0.010***	0.009***	0.009***	0.010***	0.015***	0.016***	0.017***
	(2.18)	(3.64)	(8.52)	(12.09)	(10.69)	(9.86)	(12.36)	(12.41)	(12.74)	(10.38)	(9.18)
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323
Pseudo R^2	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE A6 Quantile panel regressions – all control variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	0.05	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**
U_{Lagged}	1.003***	1.004***	1.002***	0.991***	0.986***	0.988***	0.988***	0.988***	0.985***	0.977***	0.975***
	(653.58)	(554.60)	(701.67)	(562.74)	(1317.58)	(1428.89)	(1338.83)	(1057.05)	(635.88)	(692.50)	(542.97)
Sigma	−0.072	0.139	0.250***	0.522***	0.586***	0.461***	0.483***	0.653***	1.080***	1.257***	1.431***
	(−0.31)	(1.64)	(3.05)	(6.87)	(7.08)	(6.15)	(5.53)	(5.21)	(7.81)	(6.74)	(6.08)
$\Delta lnPI$	−0.479***	−0.573***	−0.576***	−0.970***	−0.965***	−0.848***	−0.762***	−0.886***	−1.187***	−1.481***	−1.496***
	(−4.70)	(−6.71)	(−10.24)	(−13.51)	(−10.07)	(−7.82)	(−6.87)	(−6.55)	(−9.78)	(−14.09)	(−11.25)
ΔFR	−0.018***	−0.016***	−0.022***	−0.018***	−0.016***	−0.015***	−0.016***	−0.017***	−0.019***	−0.019***	−0.015***
	(−5.60)	(−7.85)	(−13.02)	(−10.37)	(−11.58)	(−11.53)	(−11.96)	(−14.20)	(−12.63)	(−8.93)	(−6.24)
HFR	0.016***	0.023***	0.024***	0.022***	0.025***	0.030***	0.039***	0.040***	0.041***	0.039***	0.043***
	(4.08)	(11.94)	(12.27)	(10.08)	(7.54)	(11.53)	(27.15)	(21.51)	(12.96)	(14.28)	(9.17)
ΔlnG	0.376***	0.350***	0.505***	0.838***	0.728***	0.540***	0.483***	0.577***	0.759***	0.730***	0.714***
	(3.51)	(4.52)	(10.28)	(15.25)	(12.38)	(9.25)	(13.02)	(13.02)	(17.33)	(11.41)	(8.18)
$\Delta lnHPI$	−0.367***	−0.421***	−0.291***	−0.478***	−0.590***	−0.552***	−0.482***	−0.493***	−0.635***	−0.748***	−0.771***
	(−3.43)	(−5.62)	(−6.48)	(−6.47)	(−9.25)	(−9.26)	(−8.16)	(−7.11)	(−8.84)	(−7.97)	(−8.47)
$\Delta lnEER$	−0.072**	−0.030*	−0.068***	−0.085***	−0.046***	−0.029***	−0.041***	−0.071***	−0.095***	−0.056***	−0.044***
	(−2.55)	(−1.78)	(−5.80)	(−6.35)	(−3.95)	(−3.47)	(−6.12)	(−8.94)	(−7.78)	(−3.56)	(−2.94)
$\Delta lnOIL$	0.001	0.001	0.002	0.006**	0.011***	0.007***	0.005***	0.003*	0.006**	0.010***	0.003
	(0.17)	(0.58)	(0.76)	(2.28)	(4.84)	(3.47)	(3.04)	(1.79)	(2.40)	(3.67)	(0.68)
lnEPU	0.001	0.002	0.005***	0.007***	0.007***	0.006***	0.007***	0.007***	0.008***	0.010***	0.010***
	(0.52)	(1.61)	(6.84)	(8.44)	(7.19)	(6.30)	(9.59)	(8.67)	(5.88)	(6.69)	(4.49)
$\Delta lnSP$	−0.014	−0.016***	−0.015***	−0.009*	−0.007*	−0.004	−0.005	−0.014***	−0.023***	−0.030***	−0.037***
	(−1.59)	(−2.98)	(−4.06)	(−1.74)	(−1.91)	(−1.55)	(−1.55)	(−3.88)	(−5.14)	(−4.46)	(−5.11)
SPRV	0.049***	0.031***	0.042***	0.045***	0.043***	0.044***	0.049***	0.068***	0.070***	0.072***	0.098***
	(5.60)	(5.70)	(9.06)	(10.15)	(7.57)	(9.29)	(10.68)	(11.82)	(7.97)	(9.15)	(3.46)
Obs	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504	15,504
N	48	48	48	48	48	48	48	48	48	48	48
T	323	323	323	323	323	323	323	323	323	323	323
Pseudo R^2	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Note: The dependent variable is the US state level unemployment rate in logistic form (U^{log}). *Sigma* is the labour reallocation index for the 9 main sectors of the US economy (σ^9). Columns 1–11 report the coefficient estimate for each quantile (τ) using the quantile panel estimator of Canay (2011) with clustered robust standard errors at the state level (based on the approach of Parente & Santos Silva, 2016). *t-statistic* in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.