Revisiting the Labor Reallocation Hypothesis for the European Countries

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Abstract

We revisit a major question which has sparked diverse perspectives in the labor economics. Specifically we examine the sectoral shift hypothesis, which was formally identified by the seminal work of Lilien, 1982. The hypothesis states that the reallocation of workers across occupations, following various shocks, that create important wage differentials, is the main factor that leads to increased unemployment. We analyze the validity of the hypothesis for 22 European countries and the time period of 1994:4 - 2023:2 using the purged Lilien's index. We take advantage of the most recent panel analysis advancements, to control for cross sectional dependence, common factors, dynamic bias and parameter heterogeneity, in an attempt to have the most robust results. Moreover we also examine for the presence of non linearities in the effect, using quantile panel analysis. Our results confirm the validity of the hypothesis using linear models, while the quantile analysis offers a more clear view of the non linear effect of labor reallocation on unemployment.

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1 Introduction

Technological change is known to be the principal driving force of economic growth. Although this positive effect is limited to the long run, in the short run the effects can be negative. In this paper, we are interested in one specific short run effect, labor reallocation, and its negative effect on employment. Starting from the seminal work of Lilien, 1982, the research on the macroeconomic effects of labor reallocation has been enriched with many papers and a variety of conclusions. The continuous advancement of econometric techniques in combination with the unprecedented macroeconomic shocks constantly revive the interest of this research question. The rise of AI technology, which increasingly replaces positions held by workers with moderate education, as well as the COVID-19 pandemic, which led to extensive use of the telecommuting option and the digitization of many services, consist of two of the most significant labor reallocation episodes. Consequently this motivates us to revisit the question regarding the effects of labor reallocation and examine these two latest episodes. Specifically we examine this question for 22 European countries using quarterly data for the time period of 1994:4 - 2023:2 controlling for cross sectional dependence, common factors and parameter heterogeneity while also testing for non linearity in this effect. Therefore we take advantage of the most recent innovations in econometrics.

The paper is organized as follows. Section 2 provides the related literature. Section 3 presents the data used, the sources, graphs and shows the results of the preliminary analysis. Section 4 explains the methodology used in the paper. Section 5 presents the empirical results of the baseline analysis. Section 6 extends the baseline analysis, with robustness checks. Section 7 presents the results of a pre Covid-19 analysis. Section 8 concludes.

2 Literature review

Technological change is the key factor causing these shifts, but it can also be attributed to shifts in consumer preferences, economic policies, etc. Changes in demand composition across sectors leads to significant wage differentials which in turn incentivizes workers to move from low-wage declining sectors to high-wage expanding sectors. This procedure, found in the literature as labor reallocation, has long troubled the researchers when it comes to its effects on unemployment. Workers wanting to move to another sector will first need to obtain the essential knowledge and skills before they are able to make the move, which may be delayed due to labor market frictions. As such labor reallocation is expected to create a temporary but significant increase in the unemployment.

This phenomenon was observed by many economists, though the first who formally identified it was David Lilien. In his seminal work Lilien, 1982, build on the model of Lucas and Prescott, 1978 and established the theoretical foundation for the sectoral shift hypothesis while also estimating a negative effect of labor reallocation, using a weighted standard deviation of sectoral employment growth rates index, on unemployment.

The next major breakthrough in the literature was achieved by Abraham and Katz, 1986. In their work they questioned the credibility of the original results. Specifically they referred to the problem of "Observational equivalence", which highlights that given the different cyclical sensitivity of sectors, the estimated impact on unemployment reflects not only the effect of labor reallocation, but aggregate shocks as well.

This sparked the literature with many proposed solutions for the estimation of the effect, "free" of aggregate shocks' influence, all of which can be found in Gallipoli and Pelloni, 2013 which offers the most complete review of the literature. Most of the papers have been based in the "purged index" approach which regresses Lilien's reallocation index on various aggregate variables in order to use the residuals as a purged index, free of aggregate influences.

Table 1 provides a summary of the literature review, which is explained in detail below

Table 1: Literature Review Summary

Paper	Index	Methodology	Conclusion
Panagiotidis, Pelloni (2014)	Purged Index	Quantile	Significant non linear effect
Bakas et al. (2016)	Purged Index	Linear Models	Significant linear effect for Europe
Gkiourkas et al. (2017)	Manufacturing Share	SVAR	Reallocation accounts for 20% of the unemployment's variation
Bakas et al. (2017)	Purged Index	Linear Models	Significant linear effect for United States
Bauer King (2018)	Theoretical Model		Labor market efficiency is negatively correlated with the effect
Vu Wu (2020)	Stock Market Dispersion	VAR	Effect lasts from 15 to 20 months
Chodorow-Reich, Wieland (2020)	Purged Index	Two Sample 2SLS	Effect is more intense during recessions due to increased frictions
Bakas et al. (2023)	Purged Index	Linear Models/ Quantile Panel	Effect is significant only for higher quantiles

Vu and Wu, 2020 construct a VAR and with the use of stock market dispersion methodology estimate that a one standard deviation shock to stock market dispersion, used to index labor reallocation, results to a significant, positive and persistent effect on unemployment, lasting 15 to 20 months. Similarly Gkiourkas et al., 2017 construct a SVAR model for the U.S. in which they are able to identify a pure reallocation shock, by imposing the right restrictions, and validate the sectoral shift hypothesis while also find that 20% of the variation of unemployment is due to reallocation shocks.

Bakas et al., 2016 and Bakas et al., 2017 take advantage of the major innovations concerning the panel analysis when cross sectional dependence is present, to validate the sectoral shift hypothesis with the Lilien's index for Europe and U.S. respectively, using a variety of models.

Departing from the use of linear models Panagiotidis and Pelloni, 2014 utilized the quantile regression by Koenker, 2005 to prove that examining only the conditional mean response of unemployment to reallocation does not provide complete information of their relationship. Instead the found that the impact of reallocation is significant only when unemployment takes high values which may be the reason we find diverse opinions in the literature of sectoral shift hypothesis. In the work of Bakas et al., 2023 the hypothesis was validated using panel data for the U.S. states utilizing both the linear and non linear methodologies mentioned above .

Recently, Chodorow-Reich and Wieland, 2020 used a reallocation index, closely related to Lilien's and in their "purging" technique, regressed it on a predicted reallocation index, constructed following Bartik, 1991, thus keeping only unexpected idiosyncratic changes in reallocation and not needing to control for each individual aggregate variable. Their results confirmed the validity of sectoral shift hypothesis, while also showing that this effect is more intense during recessions due to wage compression. Furthemore they constructed a theoretical model to prove that sticky wages and market frictions are the reasons behind the effect's significance.

Bauer and King, 2018 use the Hartz reforms of Germany to show that improvements in the labor market efficiency, which include reductions in unemployment benefits, improvements in the vocational training and job matching, can significantly reduce the impact of reallocation on unemployment. Moreover they find that aggregate skill missmatch, leads to unemployment that affects all sectors.

3 Data

The dataset consists of both time series and cross sectional data, with T = 115 and N = 22, a total of 2530 observations. We examine 22 European countries which consist of Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovenia, Spain, Sweden and the United Kingdom starting from the fourth quarter of 1994 and ending on the second quarter of 2023. The variables used consist of the unemployment rates (u), sectoral employment rates, gross domestic product (GDP), government expenditure (GE), consumer price index (CPI), interest rates (IR) and their conditional variance (h) obtained from a GARCH(1,1) model. We disaggregate the total employment (TE) into 12 sectors which consist of Agriculture-Forestry-Fishing (AFF), Industry (I), Manufacturing (M), Construction (C), Distribution trade-Repairs-Transport-Accommodation-Food services (DTAF), Information-Communication services (IC), Financial-Insurance activities (FI), Real Estate activities (RE), Professional-Scientific-Technical-Administrative-Support services (STA), Public administration-Compulsory social security-Education-Human health services (PS), Other services (OS). The data was recovered from OECD's Main Economic Indicators (MEI), except from the CPI which was recovered by WorldBank's cross country database of inflation, by Ha et al., 2021. Table 2 presents all the variables as well as their symbols.

Table 2: Variables And Their Symbols

Variable	Symbol
Sectoral Variables	
Total Employment	$TE_{i,t}$
Employment of Agriculture-Forestry-Fishing Sectors	$E_{i,t}^{AFF}$
Employment of Industrial Sector	$E_{i,t}^{I}$
Employment of Manufacturing Sector	$E_{i,t}^{M}$
Employment of Construction Sector	$E_{i,t}^{C}$
Employment of Distribution trade, Repairs, Transport, Accommodation and Food services	$E_{i,t}^{DTAF}$
Employment of Information and Communication Services	$E_{i,t}^{IC}$
Employment of Financial and Insurance activities	$E_{i,t}^{FI}$
Employment of Real Estate activities	$E_{i,t}^{RE}$
Employment of Professional, Scientific, Technical, Administrative and Support services	$E_{i,t}^{STA}$
Employment of Public administration, Compulsory social security,Education and Human health services	$E_{i,t}^{PS}$
Employment of Other services	$E_{i,t}^{OS}$
Macroeconomic Variables	
Unemployment Rate	$u_{i,t}$
Logistic form of Unemployment Rate	$u_{lg,i,t}$
Logarithmic form of Unemployment Rate	$u_{ln,i,t}$
Gross Domestic Product	$GDP_{i,t}$
Government Expenditures	$GE_{i,t}$
Consumer Price Index	$CPI_{i,t}$
Inflation	$\Delta CPI_{i,t}/I_{i,t}$
Interest Rate	$IR_{i,t}$
Interest Rate's Conditional Variance	$h_{i,t}$

Note: i indicates country, t indicates time

To facilitate the econometric analysis, we use the logarithmic u_{ln} as well as logistic u_{lg} forms of unemployment, as the latter was suggested by Wallis, 1987.

Where,

$$u_{ln,i,t} = \ln(u_{i,t}), u_{lg,i,t} = \ln(u_{i,t}/1 - u_{i,t})$$

We construct the labor reallocation index following Lilien, 1982, as a measure of between sector variance.

$$s_{i,t} = [\sum_{j=1}^{12} (\frac{E_{j,i,t}}{TE_{i,t}}) * (\ln E_{j,i,t} - \ln TE_{i,t})^2]^{1/2}$$

Where $E_{j,i,t}$ is the employment of sector j, of country i, in time t and is the total employment of the country i, in time t.

Table 3 and 4 presents the summary statistics of the sectoral employment and macroeconomic variables respectively.

Table 3: Sectoral Employment Summary Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
TE_t	9396	11274	213.8	45919	45919	45919
E_AFF_t	394.2	513.9	3.600	3332	3332	3332
E_I_t	142.5	174.4	3.400	779	779	779
E_M_t	1390	1809	31.80	8129	8129	8129
E_C_t	646.0	765.3	24.80	3331	3331	3331
E_DTAF_t	2296	2740	57.10	10247	10247	10247
E_IC_t	267.4	352.2	5.300	1556	1556	1556
E_FI_t	257.1	344.6	6.300	1302	1302	1302
E_RE_t	100.6	136.5	0.700	599	599	599
E_STA_t	1089	1486	18.20	6296	6296	6296
E_PS_t	2249	2759	35.20	12012	12012	12012
E_OS_t	563.7	805.4	9.300	3059	3059	3059

Table 4: Macroeconomic Variables Summary Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
IR_t	2.735	3.501	-0.777	29.71	29.71	29.71
ΔIR_t	-0.044	0.722	-9.647	9.128	9.128	9.128
GDP_t	802468	1.001e+06	17077	4.212e+06	4.212e+06	4.212e+06
GE_t	164485	202782	4823	919910	919910	919910
CPI_t	91.80	20.87	33.43	226.3	226.3	226.3
h_t	1.906	14.02	0.000	421.1	421.1	421.1
u_t	0.082	0.042	0.018	0.281	0.281	0.281
$u_{lg,t}$	-2.530	0.522	-3.981	-0.940	-0.940	-0.940
$u_{ln,t}$	-2.616	0.477	-3.999	-1.269	-1.269	-1.269
$\ln GDP_t$	12.78	1.371	9.745	15.25	15.25	15.25
$\Delta \ln GDP_t$	0.005	0.127	-2.789	2.550	2.550	2.550
$\ln GE_t$	11.20	1.389	8.481	13.73	13.73	13.73
$\Delta \ln GE_t$	0.004	0.127	-2.791	2.481	2.481	2.481
$\ln CPI_t$	4.495	0.220	3.510	5.422	5.422	5.422
$\ln I_t$	0.006	0.014	-0.490	0.123	0.123	0.123
s	0.006	0.006	0.000	0.065	0.065	0.065
$\hat{s}_t$	-0.000	0.007	-0.005	0.059	0.059	0.059

Figure 1 shows the time series graph of the purged labor reallocation index and unemployment giving us a picture of their relationship before undertaking formal analytical procedures. From this, we can observe a rapid increase in both the index and unemployment in the COVID-19 episode of 2020 in which the severe protection measures that were imposed by the governments significantly harmed most of the occupations while favoured these in which telecommuting was available. The rapid digitalization of government and many more services left many workers unemployed while the sectors of transportation and technology experienced the most significant development. Another such episode of lower intensity happened around 2008 which was due to the global financial crisis of 2007-2008 which had serious changes in the economic system. In particular the house market crash led to many workers reallocating from the falling sectors of construction and real estate sectors. Moreover the financial sector experienced decisive changes in an effort to avoid future similar crises.

Figure 1: Unemployment and Purged Labor Reallocation Time Series Plot

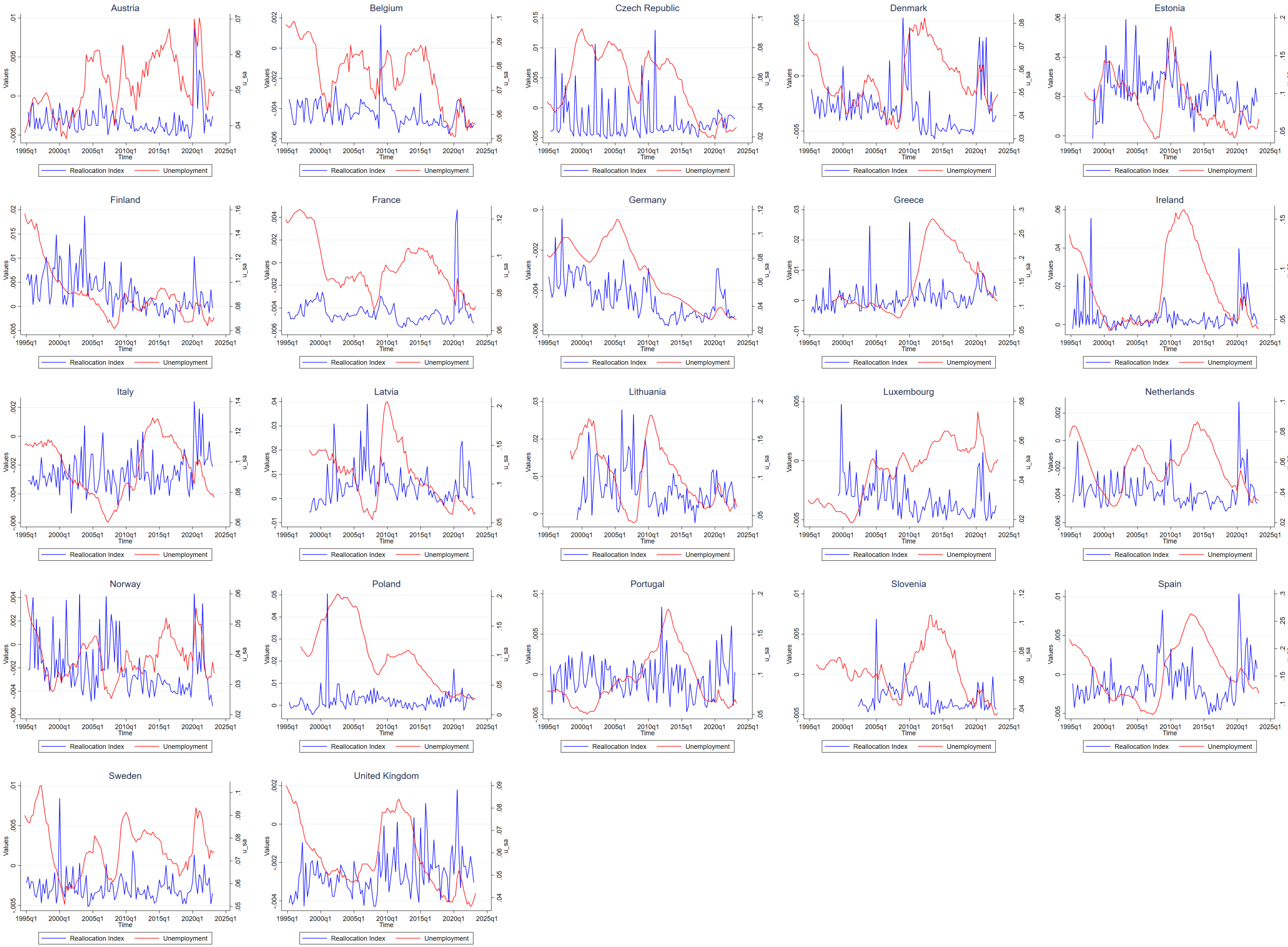


Figure 2: European Labor Reallocation Map in 2008

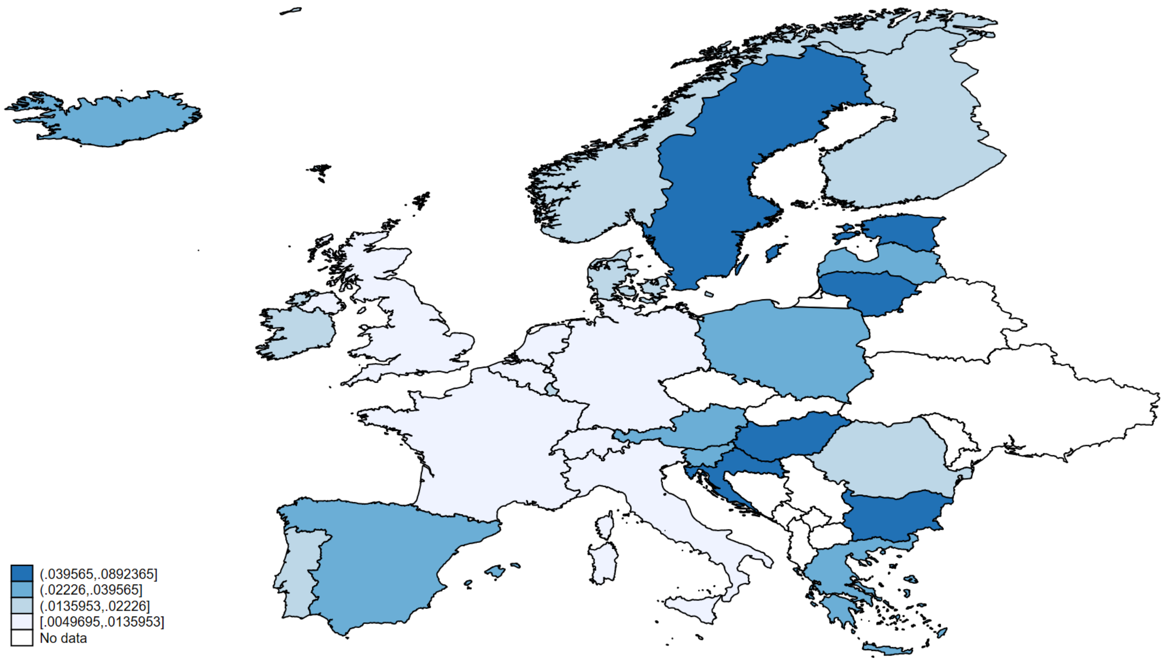


Figure 2 presents a European map which shows the intensity of labor reallocation, that the countries of our analysis, as well as some more which did not have available data for the macroeconomic variables, experienced in 2008 due to the Global Financial Crisis.

Before we move on to the main analysis we must first examine our data for the presence of unit roots, cross sectional dependence and poolability of the parameters, as these will determine how we proceed. Starting from the unit root analysis we conduct the tests of IPS by Im et al., 2003 and CIPS by Pesaran, 2007. The IPS test was developed for testing for the presence of unit roots in heterogeneous panel models where the error terms are allowed to be serially correlated. Its null hypothesis states that all the panels contain unit roots while the alternative states that some panels do not. The results are show in Table 3. By examining the p-Values of Table 3 we find that in level form only the interest rate, it's conditional variance and the labor reallocation indices have panels that do not contain unit roots. When we first differentiate the variables all are found to not contain unit roots. Similarly the CIPS test is used for testing for the presence of unit roots when the error terms are serially correlated thought it uses cross sectional averages of lagged variables and first differences to combat the problem of cross sectional dependence. As a unit root test it tests the null hypothesis of unit root presence in the variable against the alternative of stationary variable. We once again find that the only variables that do not contain unit roots in the level form are interest rate, it's conditional variance and both labor reallocation indices while in first difference form all the variables are stationary. Having said that we will continue our analysis using the first differences of the logarithms of government expenditures, GDP, CPI i.e. inflation (I). Concerning the unemployment that we found to contain a unit root, our results contradict those of Abadir et al., 2013 which found unemployment to be stationary. For this reason we will use the level form of unemployment for the main analysis and the first difference form as an extension.

Table 5: Unit Root Tests

	$u_{lg,t}$	$u_{ln,t}$	$\ln GE_t$	$\ln GDP_t$	$\ln CPI_t$	IR_t	h_t	$\hat{s}_t$	s_t
					IPS (p-Values)				
Levels	0.995	0.996	0.975	0.172	1.000	0.000***	0.000***	0.000***	0.000***
First Differences	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
					CIPS (Statistics)				
Levels	-2.006	-1.969	-1.378	-1.463	-1.616	-4.493***	-3.666***	-5.964***	-5.773***
First Differences	-5.143***	-5.261***	-4.910***	-5.704***	-4.407***	-5.499***	-5.766***	-6.190***	-6.190***

Note: The critical values for the CIPS test are -2.08, -2.16 and -2.3, for the 10%, 5% and 1% levels of significance respectively. The null hypothesis states that the variable contains a unit root.

For cross sectional dependence test we used that developed by Pesaran, 2021. The test uses the average value of the correlation coefficient of unit specific regression's error terms and its robust to panel heterogeneity and the presence of unit roots. The null hypothesis states that there is no evidence of cross sectional dependence. From Table 6 it is clear that there is significant dependence among the European countries as we can reject the null hypothesis for every variable and for every level of significance. It follows that we should use models that are able to account for cross sectional dependence in order to have efficient estimates.

Table 6: Cross Sectional Dependence Test

	$u_{lg,t}$	$u_{ln,t}$	$\ln GE_t$	$\ln GDP_t$	$\ln I_t$	IR_t	h_t	$\hat{s}_t$	s_t
					Statistic				
p-Value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Notes: The null hypothesis states that there is no evidence of cross sectional dependence.

In Table 7 we find the results of the poolability test of Chow, 1960. The test is conducted using the F statistic and the null hypothesis states that the parameters across individuals are homogeneous while under the alternative hypothesis the parameters have significant differences and should not be pooled. For both forms of unemployment we reject null hypothesis of parameter homogeneity for 10% and 5% levels of significance. As such in order to avoid biased results we must proceed with methodologies that account for parameter heterogeneity.

Table 7: Parameter Homogeneity Test

	$u_{ln,t}$	$u_{lg,t}$
Statistic	181**	179**
p-Value	0.013**	0.014**

Notes: The critical values for the Chow's test are 1.41, 1.56 and 1.86, for the 10%, 5% and 1% levels of significance respectively. The null hypothesis states that the parameters are homogeneous.

4 Methodology

In this paper we combat the issue of observational equivalence by following the approach of "purged labor reallocation index". Specifically this approach consists of separating the aggregate and idiosyncratic effects from the proposed index. This can be achieved by regressing the index on variables that proxy real and/or monetary shocks.

$$s_{i,t} = b_0 + b_1 \Delta \ln GDP_{i,t} + b_2 \Delta \ln GE_{i,t} + b_3 \Delta IR_{i,t} + b_4 h_{i,t} + b_5 \ln I_{i,t} + v_{i,t}$$

Controlling for aggregate effects we use the logarithms of growth rate of national gross domestic product $\Delta \ln GDP$, logarithms of growth rate of government expenditures $\Delta \ln GE$ and logarithm of inflation $\ln I$ to proxy real shocks, interest rate growth rates ΔIR as well as it's variance h for monetary shocks. Subsequently using the residuals $\hat{v_t}$ of the regression we have an index free of aggregate shocks' effect (the purged labor reallocation index $\hat{s_t}$).

Having resolved the major problem of endogeneity we now turn our attention to the econometric challenges imposed by the cross country correlation. Specifically when the observations between the cross sectional units are not independent from each other the estimated standard errors will be inconsistent. Although the estimated parameter is consistently estimated its significance will be affected and the inference will be incorrect. We expect common factors to be affecting simultaneously the countries of the analysis and therefore we need to account for cross sectional dependence in order to avoid misleading inference.

We follow the methodology found on Bakas et al., 2017 and Bakas et al., 2016 which propose various models that are able to control for cross sectional dependence, common factors, parameter heterogeneity and persistence.

We begin from the model of Driscoll and Kraay, 1998 which is able to control for very general forms of cross sectional dependence and correct the standard errors when the time dimension is sufficiently large. We use both the pooled OLS and fixed effects versions. A major drawback stems from its inability to account for the persistence found in the unemployment. Due to the inclusion of the lagged dependent variable in the regressors the estimated parameters may suffer from bias and the standard errors may be inefficient. The GMM estimator of Blundell and Bond, 1998 is able to correct the dynamic bias for persistent panel data though it does not directly control the problem of cross sectional dependence. Both the previous models imply the strict restriction of parameter homogeneity which if is wrongly imposed will result in inconsistent and biased results. For this reason we also use the model of Mean-Group (MG) estimator of Pesaran and Smith, 1995 which offer heterogeneous parameter estimation while being robust to dynamic bias. Furthermore we use the CCE model of Pesaran, 2006 and AMG model of Bond et al., 2006 which both can combat unobserved common factors and control for cross sectional dependence, endogeneity and autocorrelation more efficiently while allowing for parameter heterogeneity. The properties of the last two models are very similar whereas there are only certain cases in which the former leads to biased results, in contrast to the latter, according to Bond et al., 2006. For the CCE model we estimate the regression with and without country specific linear trends. Chudik and Pesaran, 2015 extend the model of Pesaran, 2006 and control for the problem of dynamic misspecifcation.

For the work to be complete the quantile panel approach is introduced in search of non linearity in the effect. Specifically if the effect of labor reallocation on unemployment is non linear then examining solely the mean response of unemployment to labor reallocation we lead to misleading results. The approach used in the paper is that of Minimum Distance Panel Quantile Estimator by Melly and Pons, 2023. This involves a two step procedure that begins by estimating cross sectional unit specific quantile regressions including a constant and then uses GMM procedure to regress the fitted values to all the independent variables.

The regression estimated by all the models, has the unemployment rates (u_t) as dependent variable, while the independents consist of the dependent's variable lag (u_{t-1}), purged labor reallocation index ($\hat{s_t}$), logarithm of GDP growth rates ($\Delta\ln GDP_t$), government expenditures logarithmic first differences ($\Delta\ln GE_t$), logarithm of inflation ($\ln I_t$), interest rate first differences (ΔIR_t) and its conditional variance (h).

$$u_{i,t} = b_0 + b_1 + b_2\Delta\ln GDP_{i,t} + b_3\Delta\ln GE_{i,t} + b_4\Delta IR_{i,t} + b_5 h_{i,t} + b_6\ln I_{i,t} + e_{i,t}$$

As such we follow the analyses of Bakas et al., 2017 and Bakas et al., 2016, while we allow the model to endogenously select the optimal lags needed in our robustness checks.

5 Empirical Results

5.1 Linear Models

Starting off it is important to mention that across the two forms of unemployment used, the results remain extremely similar. The significance of the variables found in Tables 8 and 9 are exactly the same while the difference of the estimated coefficients is insignificant. In the first model of Driscoll and Kraay, 1998 we find the labor reallocation index to be statistically insignificant using pooled

OLS and barely significant using fixed effects for levels of significance only higher that 10%. As mentioned before this is highly likely due to the model being able to only capture general forms of cross sectional dependence. In contrast the GMM estimator of Blundell and Bond, 1998 estimates a highly significant effect of the index with the coefficient being 1.942 and 1.824 for the logistic and logarithmic form respectively. The Mean Group estimator finds the effect to be highly significant as well while the estimated coefficient is significantly higher at 3.562 and 3.296. The models of AMG and CCE with and without the inclusion of country specific linear trend estimate a significant and very similar coefficient, between 2 and 2.4, for the effect of labor reallocation on unemployment proving their similar properties. Interesting results are found by the dynamic CCE model which finds the effect to be significant for levels of significance only higher than 10% while the coefficient is much more modest than the previous results, being at 1.627 and 1.467 for the logistic and logarithmic form respectively.

Concerning the control variables we find that only the GDP growth rates to be consistently significant with negative sign even for 10% level of significance which showcases the effect of demand shocks on unemployment. The increased demand will lead to the firms extending their use of workers, in their effort to increase the profits, which will lead to lower unemployment. The coefficient varies from -0.85 in MG and AMG models to -0.35 in the CCE models. The interest rate growth rate and it's variance are found to be significant for most models except the CCE models making unclear whether monetary shocks have true effects on unemployment. For the government expenditure growth rates which proxy the fiscal policy we only find significant effect in the CCE models with a coefficient similar to the GDP growth rates leading once again in unclear results about the effects of government fiscal actions in combating unemployment. Lastly the effect of supply shocks proxied by the inflation is found significant and negative only by the GMM, MG and AMG models.

Table 8: Logistic Unemployment Linear Model Estimations

$u_{lg,t}$	DKFE	DKPOLS	BB	MG	AMG	CCE	CCE w.trend	dynCCE
$u_{lg,t-1}$	0.989***	0.983***	0.954***	0.967***	0.951***	0.945***	0.933***	0.879***
	(0.006)	(0.009)	(0.008)	(0.007)	(0.008)	(0.013)	(0.016)	(0.031)
$\hat{s}_t$	0.705	1.867*	1.942***	3.562***	2.405***	2.398***	2.213***	1.627*
	(0.723)	-1.041	(0.304)	(0.805)	(0.732)	(0.788)	(0.721)	(0.891)
$\Delta\ln GDP_t$	-0.722*	-0.695*	-0.295***	-0.893***	-0.802***	-0.381*	-0.351*	-0.344**
	(0.374)	(0.379)	(0.065)	(0.175)	(0.184)	(0.203)	(0.198)	(0.149)
$\Delta\ln GE_t$	-0.034	-0.050	0.013	-0.261	-0.198	-0.371***	-0.354**	-0.105
	(0.256)	(0.244)	(0.090)	(0.185)	(0.182)	(0.140)	(0.138)	(0.179)
ΔIR_t	-0.010**	-0.011**	-0.002	-0.020***	-0.013***	-0.003	-0.003	0.004
	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)	(0.011)
h_t	0.000***	0.000**	0.000***	0.006***	0.002	0.001	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
$\ln I_t$	-0.001	-0.001	-0.001**	-0.006***	-0.003*	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	2362	2362	1768	2362	2362	2362	2362	2318
RMSE	0.054	0.054	0.043	0.058	0.054	0.047	0.047	0.046
R^2	0.025	0.025	0.043	0.025	0.025	0.024	0.031	0.041

Note: Standard errors in parentheses. $\hat{s}_t$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively.

Table 9: Logarithmic Unemployment Linear Model Estimations

$u_{ln,t}$	DKFE	DKPOLS	BB	MG	AMG	CCE	CCE w.trend	dynCCE
$u_{ln,t-1}$	0.989***	0.983***	0.950***	0.967***	0.952***	0.945***	0.933***	0.877***
	(0.006)	(0.010)	(0.008)	(0.007)	(0.007)	(0.013)	(0.016)	(0.031)
$\hat{s_t}$	0.642	1.695*	1.824***	3.296***	2.255***	2.194***	2.016***	1.467*
	(0.658)	(0.945)	(0.284)	(0.757)	(0.700)	(0.746)	(0.680)	(0.837)
$\Delta\ln GDP_t$	-0.659*	-0.634*	-0.264***	-0.827***	-0.740***	-0.347*	-0.320*	-0.311**
	(0.343)	(0.347)	(0.061)	(0.162)	(0.171)	(0.191)	(0.186)	(0.141)
$\Delta\ln GE_t$	-0.019	-0.033	0.022	-0.220	-0.172	-0.329***	-0.314**	-0.070
	(0.232)	(0.220)	(0.084)	(0.167)	(0.166)	(0.127)	(0.125)	(0.168)
ΔIR_t	-0.010**	-0.010**	-0.002	-0.018***	-0.012***	-0.003	-0.003	0.004
	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.005)	(0.005)	(0.010)
h_t	0.000***	0.000**	0.000***	0.005***	0.002	0.001	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
$\ln I_t$	-0.001	-0.001	-0.001**	-0.005***	-0.003*	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2362	2362	1768	2362	2362	2362	2362	2318
RMSE	0.054	0.054	0.043	0.054	0.054	0.044	0.044	0.043
R^2	0.025	0.025	0.043	0.025	0.025	0.033	0.032	0.043

Note: Standard errors in parentheses. $\hat{s_t}$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively.

5.2 Quantile Panel

The mixed results obtained by the linear models justify the use of quantile regression to examine the effect of labor reallocation on more quantiles rather than focus only on the effect of the mean quantile i.e. the 0.5 quantile. The results obtained by the use of Minimum Distance Panel Quantile Estimator by Melly and Pons, 2023 for both forms of unemployment are shown in Table 10 and 11.

Tables 10 and 11 make clear the existence of non linear effect of labor reallocation on unemployment. The results remain similar between the two forms of unemployment used. Specifically we can observe that the significance of the labor reallocation index is very volatile across quantiles. Starting with a highly significant effect in the 10% quantile. As we move to the median quantile the significance gets weaker. It is very important to note that for the median quantile the effect is found to be non significant which may explain why we get so diverse results from the linear models used previously. Moving to higher quantiles the significance is found to be once again extremely strong, as for all the quantiles above 50% we cannot reject the null hypothesis of non significance. The coefficient of the effect of labor reallocation shows a steady growth as we move to higher quantiles starting from a modest estimation of 0.6 at the 10% quantile and ending more than three times higher at the 90% quantile at 2.2. This proves that the relationship between labor reallocation and unemployment is significantly non linear. As such we find that for average unemployment rates, labor reallocation episodes can change the current allocation of workers across sectors without leading to increased unemployment. In contrast when the timing of these episodes coincides with relatively low or high rates of unemployment the workers cannot efficiently change their occupation across sectors thus leading to a prolonged state of job searching and an increase in unemployment.

When it comes to the control variables we find a non linear effect of the monetary policy on unemployment. More precisely the interest rate growth rates can achieve lower unemployment only for low to average unemployment rate i.e. for quantiles lower that 60%. with the effect being stronger for median quantiles. The conditional variance of the interest rates has a significant effect only for low unemployment. Similarly the fiscal policy is found to decrease unemployment only when the latter is low with the effect becoming insignificant for quantiles higher that 20%.

Table 10: Logistic Unemployment Quantile Panel Estimations

Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
$u_{lg,t-1}$	1.156***	1.174***	1.207***	1.195***	1.212***	1.228***	1.223***	1.241***	1.228***
	(0.0621)	(0.0583)	(0.0547)	(0.0521)	(0.0551)	(0.0549)	(0.0589)	(0.0636)	(0.0692)
$u_{lg,t-2}$	-0.156***	-0.180***	-0.217***	-0.203***	-0.227***	-0.247***	-0.245***	-0.267***	-0.262***
	(0.0585)	(0.0567)	(0.0525)	(0.0510)	(0.0541)	(0.0538)	(0.0570)	(0.0614)	(0.0665)
$\hat{s}_t$	0.672***	0.555**	0.560**	0.732**	0.832	1.229***	1.741***	2.472***	2.031**
	(0.148)	(0.216)	(0.273)	(0.313)	(0.533)	(0.270)	(0.430)	(0.605)	(0.866)
ΔIR_t	-0.00881**	-0.00941***	-0.0104***	-0.00943***	-0.0104***	-0.00786***	-0.00551*	-0.00374	-0.00345
	(0.00379)	(0.00333)	(0.00386)	(0.00290)	(0.00270)	(0.00250)	(0.00304)	(0.00366)	(0.00538)
h_t	0.000375***	0.000286**	0.000104	8.35e-05	6.69e-05	6.49e-05	5.77e-05	0.000121	2.84e-05
	(0.000140)	(0.000144)	(0.000107)	(8.58e-05)	(8.07e-05)	(4.88e-05)	(4.97e-05)	(0.000143)	(0.000106)
$\Delta \ln GDP_t$	-0.606***	-0.586***	-0.701***	-0.659***	-0.665***	-0.663***	-0.723***	-0.726***	-0.775***
	(0.193)	(0.177)	(0.188)	(0.189)	(0.197)	(0.199)	(0.195)	(0.222)	(0.281)
$\Delta \ln GDP_t - 1$	-1.384***	-1.221***	-1.070***	-1.017***	-0.952***	-0.932***	-0.928***	-0.912***	-0.846***
	(0.197)	(0.163)	(0.144)	(0.126)	(0.138)	(0.111)	(0.120)	(0.134)	(0.175)
$\Delta \ln GE_t$	-0.580**	-0.363**	-0.169	-0.0372	0.0229	0.0118	0.0748	0.245	0.263
	(0.253)	(0.177)	(0.173)	(0.175)	(0.177)	(0.177)	(0.174)	(0.176)	(0.228)
$\ln I_t$	-0.0549	0.00908	-0.0489	-0.0775	-0.0418	-0.100	-0.0218	0.0489	0.0942
	(0.144)	(0.100)	(0.129)	(0.138)	(0.134)	(0.184)	(0.155)	(0.128)	(0.143)
Observations	2,354	2,354	2,354	2,354	2,354	2,354	2,354	2,354	2,354
RMSE	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054
R^2	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025

Note: Standard errors in parentheses. $\hat{s}_t$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively. The model used is the Minimum Distance Panel Quantile Estimator by Melly and Pons, 2023.

Table 11: Logarithmic Unemployment Quantile Panel Estimations

Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
$u_{lg,t-1}$	1.159***	1.171***	1.202***	1.194***	1.211***	1.225***	1.217***	1.220***	1.214***
	(0.062)	(0.057)	(0.055)	(0.051)	(0.055)	(0.055)	(0.060)	(0.066)	(0.068)
$u_{lg,t-2}$	-0.153***	-0.173***	-0.209***	-0.200***	-0.226***	-0.244***	-0.241***	-0.247***	-0.254***
	(0.058)	(0.056)	(0.052)	(0.050)	(0.054)	(0.054)	(0.058)	(0.063)	(0.065)
$\hat{s}_t$	0.575***	0.410**	0.444*	0.679**	0.754	1.118***	1.575***	2.070***	2.208**
	(0.155)	(0.203)	(0.234)	(0.289)	(0.489)	(0.235)	(0.386)	(0.630)	(0.941)
ΔIR_t	-0.008**	-0.008***	-0.009***	-0.009***	-0.009***	-0.007***	-0.005**	-0.004	-0.003
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
h_t	0.000***	0.000**	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta \ln GDP_t$	-0.561***	-0.526***	-0.644***	-0.609***	-0.610***	-0.615***	-0.667***	-0.641***	-0.723***
	(0.172)	(0.159)	(0.172)	(0.175)	(0.181)	(0.182)	(0.180)	(0.192)	(0.248)
$\Delta \ln GDP_t - 1$	-1.258***	-1.120***	-0.974***	-0.931***	-0.869***	-0.864***	-0.853***	-0.848***	-0.794***
	(0.185)	(0.152)	(0.131)	(0.114)	(0.126)	(0.100)	(0.111)	(0.126)	(0.158)
$\Delta \ln GE_t$	-0.496**	-0.306*	-0.143	-0.030	0.026	0.023	0.072	0.211	0.208
	(0.233)	(0.159)	(0.159)	(0.162)	(0.160)	(0.156)	(0.158)	(0.159)	(0.197)
$\ln I_t$	-0.060	-0.013	-0.045	-0.087	-0.035	-0.094	-0.013	0.076	0.108
	(0.125)	(0.091)	(0.117)	(0.135)	(0.119)	(0.169)	(0.139)	(0.099)	(0.130)
Observations	2,354	2,354	2,354	2,354	2,354	2,354	2,354	2,354	2,354
RMSE	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054
R^2	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025

Note: Standard errors in parentheses. $\hat{s}_t$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively. The model used is the Minimum Distance Panel Quantile Estimator by Melly and Pons, 2023.

6 Robustness Check

To validate robustly the sectoral shift hypothesis, we include 2 robustness checks.

6.1 Endogenous Optimal Lag Selection

In the first robustness check, we allow the model to endogenously select the optimal lags needed. Specifically the Bayesian Information Criteria (BIC) estimated the ARDL model with two lags of unemployment and one of GDP, to be the optimal. The major difference that we find, in Tables 12 and 13 in contrast to the baseline analysis, is that the effect of labor reallocation is now found consistently significant by all models, except from the DK POLS. This applies even for the dynamic CCE model, which in the previous analysis estimated the index to be significant for 10% level of significance. The coefficient of the effect is estimated by the various models, much weaker being between 0.9 and 2, in contrast to the baseline analysis in which was estimated between 1.8 and 3.5. The effect of demand shocks has major differences as well, as it is now found extremely significant by all models. The monetary shocks proxies, are found significant by more models, thought not consistently, leading once again to uncertainty about their effect. The inflation and government expenditures have weak signs of significance. The coefficient differences with the baseline analysis can be observed more clearly in Figure 3

Table 12: Logistic Unemployment Optimal Lag Linear Model Estimates

$u_{lg,t}$	DKFE	DKPOLS	BB	MG	AMG	CCE	CCE w.trend	dynCCE
$\hat{s}_t$	1.291**	0.735*	1.485***	1.761***	0.920**	2.002***	1.941**	1.606**
	(0.564)	(0.434)	(0.308)	(0.665)	(0.393)	(0.756)	(0.788)	(0.774)
ΔIR_t	-0.007**	-0.006**	-0.000	-0.012***	-0.010***	-0.009*	-0.010**	-0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.005)	(0.005)	(0.009)
h_t	0.000**	0.000**	0.000**	0.002	0.001	0.002*	0.002**	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$\Delta\ln GDP_t$	-0.750***	-0.756***	-0.665***	-0.917***	-0.793***	-0.447**	-0.433**	-0.300**
	(0.146)	(0.141)	(0.070)	(0.178)	(0.118)	(0.201)	(0.202)	(0.130)
$\Delta\ln GDP_{t-1}$	-1.065***	-1.065***	-0.960***	-1.000***	-0.425***	-0.920***	-0.910***	-0.335*
	(0.124)	(0.116)	(0.061)	(0.117)	(0.142)	(0.107)	(0.102)	(0.200)
$\Delta\ln GE_t$	-0.032	-0.005	0.068	-0.274**	-0.002	-0.251*	-0.256*	-0.165
	(0.197)	(0.198)	(0.091)	(0.125)	(0.002)	(0.144)	(0.146)	(0.132)
$\ln I_t$	-0.000	-0.000	-0.001	-0.003**	0.095***	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.015)	(0.002)	(0.002)	(0.003)
$u_{lg,t-1}$	1.201***	1.209***	1.015***	1.216***	1.146***	1.118***	1.101***	0.965***
	(0.051)	(0.052)	(0.016)	(0.059)	(0.074)	(0.070)	(0.071)	(0.075)
$u_{lg,t-2}$	-0.220***	-0.221***	-0.065***	-0.245***	-0.211***	-0.178***	-0.178***	-0.063
	(0.053)	(0.052)	(0.016)	(0.056)	(0.067)	(0.062)	(0.061)	(0.063)
Observations	2354	2354	1764	2354	2354	2354	2354	2244
RMSE	0.043	0.043	0.043	0.052	0.049	0.050	0.050	0.044
R^2	0.043	0.043	0.043	0.019	0.020	0.034	0.033	0.057

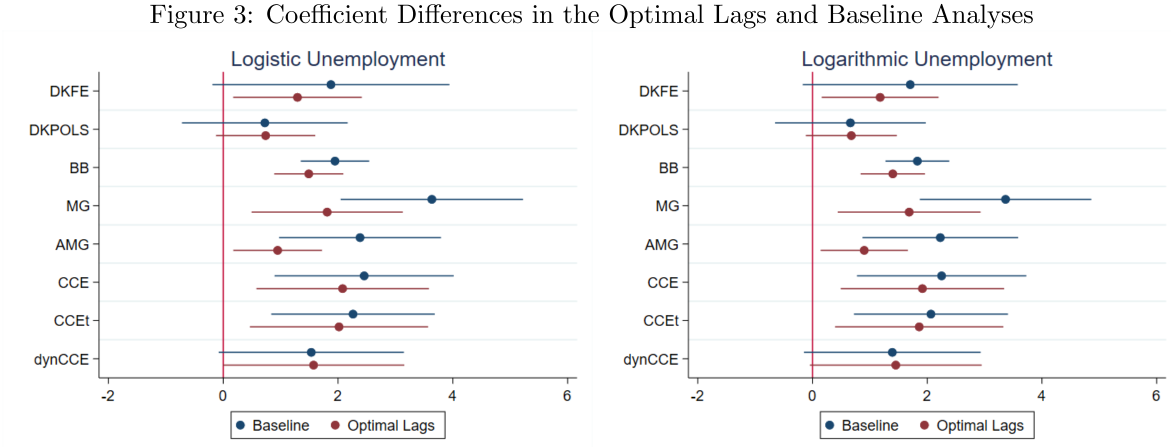
Note: Standard errors in parentheses. $\hat{s}_t$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively.

Table 13: Logarithmic Unemployment Optimal Lag Linear Model Estimates

$u_{ln,t}$	DKFE	DKPOLS	BB	MG	AMG	CCE	CCE w.trend	dynCCE
$\hat{s}_t$	1.176**	0.672*	1.394***	1.637***	0.876**	1.839**	1.786**	1.477**
	(0.512)	(0.399)	(0.287)	(0.628)	(0.384)	(0.717)	(0.745)	(0.730)
ΔIR_t	-0.006**	-0.006**	-0.000	-0.011***	-0.009***	-0.008*	-0.009**	0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.008)
h_t	0.000**	0.000**	0.000**	0.002	0.001	0.002*	0.002**	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$\Delta \ln GDP_t$	-0.688***	-0.693***	-0.606***	-0.853***	-0.740***	-0.415**	-0.401**	-0.277**
	(0.134)	(0.130)	(0.065)	(0.167)	(0.110)	(0.189)	(0.190)	(0.122)
$\Delta \ln GDP_{t-1}$	-0.983***	-0.983***	-0.888***	-0.934***	-0.380***	-0.857***	-0.847***	-0.312*
	(0.112)	(0.104)	(0.057)	(0.109)	(0.132)	(0.101)	(0.096)	(0.188)
$\Delta \ln GE_t$	-0.020	0.004	0.071	-0.240**	-0.002	-0.222*	-0.228*	-0.131
	(0.180)	(0.181)	(0.084)	(0.115)	(0.002)	(0.133)	(0.134)	(0.125)
$\ln I_t$	-0.000	-0.000	-0.001	-0.003**	0.093***	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.015)	(0.002)	(0.002)	(0.003)
$u_{ln,t-1}$	1.194***	1.202***	1.007***	1.214***	1.144***	1.115***	1.097***	0.962***
	(0.050)	(0.051)	(0.016)	(0.059)	(0.075)	(0.070)	(0.071)	(0.075)
$u_{ln,t-2}$	-0.213***	-0.215***	-0.061***	-0.243***	-0.208***	-0.175***	-0.175***	-0.061
	(0.052)	(0.051)	(0.016)	(0.056)	(0.067)	(0.062)	(0.061)	(0.063)
Observations	2354	2354	1764	2354	2354	2354	2354	2244
RMSE	0.043	0.043	0.043	0.049	0.049	0.046	0.046	0.041
R^2	0.043	0.043	0.043	0.020	0.020	0.035	0.035	0.059

Note: Standard errors in parentheses. $\hat{s}_t$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively.

Figure 3: Coefficient Differences in the Optimal Lags and Baseline Analyses



6.2 First Differences

In the last robustness check, we conduct the same analysis, using the first differences of unemployment. As we already saw in the data section, unemployment was found to contain a unit root. Even though previous works consider unemployment to be stationary, if the opposite is true then our results will be extremely misleading. In Table 14 and 15 the AMG model now estimates the reallocation index to have insignificant effect, while the opposite is true for the dynamic CCE model, which estimates a significant effect for a 5% level. As such, even if we use the first differences of unemployment, which are found stationary by every unit root test, the results remain the same, the effect of reallocation is significant.

Table 14: Logistic Unemployment First Difference Linear Model Estimates

$\Delta u_{lg,t}$	DKFE	DKPOLS	BB	MG	AMG	CCE	CCE w.trend	dynCCE
$\hat{s}_t$	1.268**	0.571	1.406***	1.929***	0.131	1.577**	1.583**	1.917**
	(0.568)	(0.424)	(0.301)	(0.593)	(0.214)	(0.630)	(0.685)	(0.813)
ΔIR_t	-0.005*	-0.005*	-0.001	-0.010***	-0.002	-0.007	-0.007	0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.005)	(0.005)	(0.008)
h_t	0.000**	0.000**	0.000	0.002*	-0.001	0.003**	0.003**	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$\Delta\ln GDP_t$	-0.794***	-0.780***	-0.574***	-1.006***	-0.537***	-0.538**	-0.534**	-0.693***
	(0.157)	(0.146)	(0.067)	(0.177)	(0.166)	(0.228)	(0.224)	(0.214)
$\Delta\ln GDP_{t-1}$	-1.083***	-1.071***	-0.944***	-1.036***	-0.519***	-0.987***	-1.013***	-0.614***
	(0.127)	(0.117)	(0.062)	(0.127)	(0.096)	(0.124)	(0.121)	(0.205)
$\Delta\ln GE_t$	0.033	0.050	0.178**	-0.141	-0.273**	-0.150	-0.151	-0.134
	(0.204)	(0.205)	(0.087)	(0.123)	(0.114)	(0.151)	(0.155)	(0.137)
$\ln I_t$	0.000	0.000	-0.001	-0.002	0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
$\Delta u_{lg,t-1}$	0.209***	0.216***	-0.078***	0.236***	0.104	0.177***	0.171***	0.046
	(0.052)	(0.052)	(0.018)	(0.058)	(0.068)	(0.065)	(0.065)	(0.067)
Observations	2354	2354	1764	2354	2354	2354	2354	2244
RMSE	0.041	0.041	0.041	0.053	0.049	0.051	0.051	0.045
R^2	0.059	0.059	0.059	0.585	0.589	0.699	0.691	0.772

Note: Standard errors in parentheses. $\hat{s}_t$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively.

Table 15: Logarithmic Unemployment First Difference Linear Model Estimates

$\Delta u_{ln,t}$	DKFE	DKPOLS	BB	MG	AMG	CCE	CCE w.trend	dynCCE
$\hat{s}_t$	1.157**	0.523	1.344***	1.797***	0.097	1.464**	1.463**	1.794**
	(0.516)	(0.387)	(0.281)	(0.558)	(0.201)	(0.595)	(0.648)	(0.766)
ΔIR_t	-0.005*	-0.005*	-0.001	-0.010***	-0.002	-0.006	-0.006	0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.008)
h_t	0.000**	0.000***	0.000	0.002*	-0.001	0.002**	0.002**	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta\ln GDP_t$	-0.729***	-0.717***	-0.523***	-0.936***	-0.492***	-0.499**	-0.496**	-0.642***
	(0.144)	(0.134)	(0.063)	(0.166)	(0.155)	(0.214)	(0.211)	(0.203)
$\Delta\ln GDP_{t-1}$	-1.000***	-0.989***	-0.880***	-0.967***	-0.474***	-0.921***	-0.945***	-0.567***
	(0.114)	(0.106)	(0.058)	(0.118)	(0.088)	(0.116)	(0.115)	(0.192)
$\Delta\ln GE_t$	0.039	0.054	0.165**	-0.121	-0.246**	-0.130	-0.130	-0.101
	(0.188)	(0.188)	(0.081)	(0.114)	(0.105)	(0.140)	(0.143)	(0.132)
$\ln I_t$	0.000	0.000	-0.001	-0.001	0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
$\Delta u_{ln,t-1}$	0.202***	0.209***	-0.080***	0.234***	0.099	0.173***	0.167**	0.044
	(0.051)	(0.051)	(0.018)	(0.058)	(0.069)	(0.065)	(0.066)	(0.067)
Observations	2354	2354	1764	2354	2354	2354	2354	2244
RMSE	0.041	0.041	0.041	0.049	0.049	0.048	0.048	0.042
R^2	0.059	0.059	0.059	0.589	0.589	0.703	0.695	0.775

Note: Standard errors in parentheses. $\hat{s}_t$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively.

7 Pre Covid-19 Period

Lastly we examine how the estimations change if we do not include, the most significant episode of labor reallocation, the COVID-19 crisis. Specifically we constraint our sample, excluding every observation from 2020 and later.

From Tables 16 and 17, we find the reallocation index to be consistently significant for 5% level of significance and not for 1%. The estimated coefficient remains stable across the pre Covid-19 analysis and the optimal lag selection robustness check. The coefficient of GDP is significantly increased, which shows that demand shocks had much stronger effect in the pre COVID-19 period. The last difference lies in the government expenditures, which are now found significant by both the DK versions and the BB model. The coefficient differences are depicted in the Figure 4. From this we conclude that the Covid-19 crisis, may reinforced the effect of reallocation on unemployment, though the effect was always significant.

Table 16: Logistic Unemployment Linear Model Estimates for the Pre Covid-19 Time Period

$u_{lg,t}$	DKFE	DKPOLS	BB	MG	AMG	CCE	CCE w.trend	dynCCE
$\hat{s}_t$	1.239**	0.673	1.266***	1.466**	0.909**	2.029***	1.821**	2.354**
	(0.570)	(0.413)	(0.286)	(0.645)	(0.354)	(0.724)	(0.750)	-1.083
ΔIR_t	-0.006*	-0.006*	-0.000	-0.012***	-0.007**	-0.012**	-0.011*	-0.004
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)	(0.007)
h_t	0.000**	0.000**	0.000**	0.002*	0.001	0.003**	0.002**	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
$\Delta \ln GDP_t$	-1.020***	-0.990***	-1.073***	-1.230***	-0.936***	-0.924***	-0.950***	-0.654***
	(0.187)	(0.193)	(0.107)	(0.228)	(0.155)	(0.216)	(0.209)	(0.249)
$\Delta \ln GDP_{t-1}$	-1.143***	-1.108***	-1.179***	-1.004***	-0.974***	-0.748***	-0.849***	-0.419
	(0.176)	(0.178)	(0.105)	(0.191)	(0.164)	(0.188)	(0.187)	(0.287)
$\Delta \ln GE_t$	-0.334***	-0.293**	-0.321***	-0.268**	-0.154	-0.151	-0.189	-0.273
	(0.116)	(0.118)	(0.098)	(0.111)	(0.126)	(0.132)	(0.119)	(0.192)
$\ln I_t$	-0.066	-0.020	-0.756***	-0.301*	-0.169	-0.314	-0.480**	-0.448
	(0.166)	(0.167)	(0.163)	(0.161)	(0.147)	(0.203)	(0.210)	(0.321)
$u_{lg,t-1}$	1.204***	1.219***	0.992***	1.192***	1.120***	1.070***	1.048***	0.914***
	(0.052)	(0.051)	(0.018)	(0.062)	(0.074)	(0.070)	(0.067)	(0.066)
$u_{lg,t-2}$	-0.223***	-0.231***	-0.051***	-0.219***	-0.171**	-0.131**	-0.123**	-0.030
	(0.055)	(0.052)	(0.018)	(0.061)	(0.068)	(0.062)	(0.059)	(0.058)
Observations	2068	2068	1566	2068	2068	2068	2068	1958
RMSE	0.042	0.042	0.042	0.049	0.045	0.046	0.046	0.042
R^2	0.775	0.775	0.775	0.018	0.019	0.038	0.037	0.106

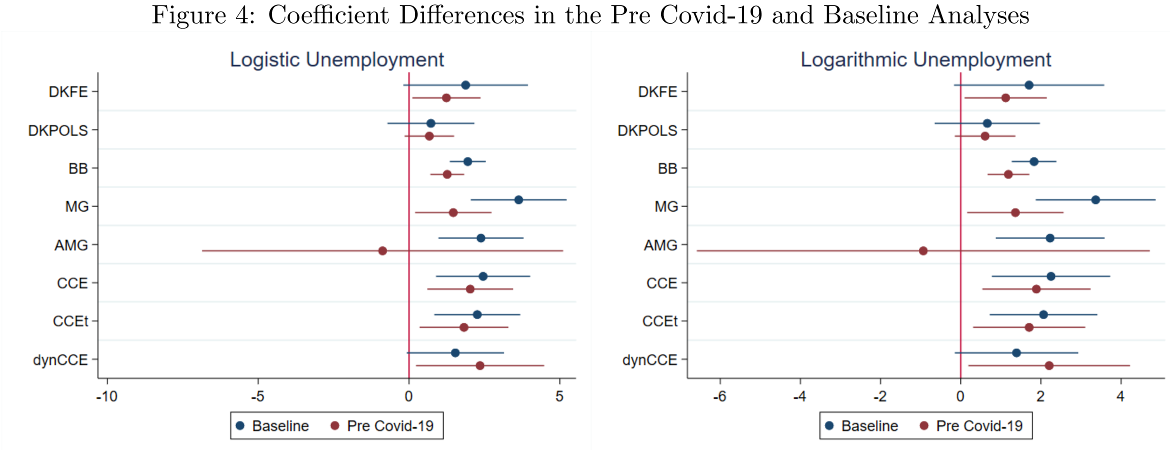
Note: Standard errors in parentheses. $\hat{s}_t$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively.

Table 17: Logarithmic Unemployment Linear Model Estimates for the Pre Covid-19 Time Period

$u_{ln,t}$	DKFE	DKPOLS	BB	MG	AMG	CCE	CCE w.trend	dynCCE
$\hat{s}_t$	1.121**	0.606	1.188***	1.362**	0.821**	1.887***	1.706**	2.206**
	(0.516)	(0.381)	(0.266)	(0.613)	(0.353)	(0.688)	(0.713)	(1.027)
ΔIR_t	-0.006*	-0.005*	-0.000	-0.011***	-0.006**	-0.012**	-0.010*	-0.003
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)	(0.006)
h_t	0.000**	0.000**	0.000**	0.002*	0.001	0.002**	0.002**	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
$\Delta \ln GDP_t$	-0.934***	-0.907***	-0.986***	-1.120***	-0.867***	-0.833***	-0.856***	-0.577***
	(0.174)	(0.179)	(0.099)	(0.194)	(0.148)	(0.185)	(0.179)	(0.215)
$\Delta \ln GDP_{t-1}$	-1.040***	-1.008***	-1.076***	-0.926***	-0.910***	-0.686***	-0.775***	-0.369
	(0.162)	(0.164)	(0.097)	(0.180)	(0.154)	(0.180)	(0.179)	(0.257)
$\Delta \ln GE_t$	-0.293***	-0.257**	-0.285***	-0.233**	-0.115	-0.128	-0.164	-0.227
	(0.109)	(0.111)	(0.091)	(0.103)	(0.115)	(0.122)	(0.109)	(0.177)
$\ln I_t$	-0.051	-0.014	-0.689***	-0.277*	-0.158	-0.279	-0.434**	-0.421
	(0.152)	(0.153)	(0.151)	(0.152)	(0.138)	(0.191)	(0.197)	(0.295)
$u_{ln,t-1}$	1.197***	1.212***	0.982***	1.191***	1.118***	1.067***	1.045***	0.916***
	(0.052)	(0.051)	(0.018)	(0.063)	(0.074)	(0.071)	(0.068)	(0.067)
$u_{ln,t-2}$	-0.216***	-0.224***	-0.044**	-0.217***	-0.169**	-0.128**	-0.120**	-0.033
	(0.056)	(0.052)	(0.018)	(0.061)	(0.068)	(0.063)	(0.060)	(0.058)
Observations	2068	2068	1566	2068	2068	2068	2068	1958
RMSE	0.042	0.042	0.042	0.045	0.045	0.043	0.042	0.039
R^2	0.775	0.775	0.775	0.019	0.019	0.039	0.038	0.108

Note: Standard errors in parentheses. $\hat{s}_t$ denotes the purged labor reallocation index. RMSE denotes the Root Mean Square Error. T = 115 and N = 22. ***, ** and * denote statistical significance at 1%, 5% and 10% levels of significance respectively.

Figure 4: Coefficient Differences in the Pre Covid-19 and Baseline Analyses



8 Conclusion

The major advancements that the cross sectional dependent panel analysis experienced in the recent period, gave us the opportunity to use a variety of models and attempt to achieve the most robust results when examining for the sectoral shift hypothesis. In combination with the quantile panel advancements, we are able to confirm the validity of sectoral shift hypothesis. When shocks, like technological shocks or changes in the demand composition, create significant wage differentials, many workers will find it profitable to change their occupation. The market frictions, downward rage rigidity and required skills and knowledge leads to short run unemployment. Using various linear models as well as non linear quantile panel analysis we are able to confirm the validity of this effect. We find that the between-occupation labor reallocation index, of Lilien, 1982 after it has been purged from aggregate effects, has significant effect on unemployment. Most of the models considered found the effect to be significant for either 1% or 5% levels of significance, with the coefficient ranging from 1.8 and 3.3. Furthermore, in order to have completely robust results, we switch from the linear analysis and employ a panel quantile model to find significant non linearities in the effect of labor reallocation on unemployment. In particular we find that for the median 50% quantile, the effect is insignificant, which justifies why the linear models offer diverse results. The effect is estimated significant only for 5% levels of significant for quantiles lower than 50% , while for quantiles higher than 50% the effect is extremely significant. The coefficient starts from 0.5 in the lowest 10% quantile and ends to 2.2 in the highest 90% quantile. We also conduct robustness checks, by allowing the model to endogenously select the optimal lags needed as well as using first differences of unemployment. None of these analyses provides a contradicting significance of the effect. Finally we analyze the effect for the pre Covid-19 time period, which again does not change the validity of the hypothesis.

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