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"Employment uncertainty a year after the irruption of the covid-19 pandemic"

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Abstract

This paper examines the evolution of consumer uncertainty about unemployment one year after the irruption of the covid-19 pandemic in European countries. Since uncertainty is not directly observable, we use two alternative methods to directly approximate it. Both approaches are based on qualitative expectations elicited form the consumer survey conducted by the European Commission. On the one hand, following Dibiasi and Iselin (2019), we use the share of consumers unable to formalize expectations about unemployment (Knightian-type uncertainty). On the other hand, we use the geometric discrepancy indicator proposed by Claveria et al. (2019) to quantify the proportion of disagreement in business and consumer expectations. We have used information from 22 European countries. We find that both uncertainty measures covary. Although we observe marked differences across countries, in most cases the perception of employment uncertainty peaked before the outbreak of the crisis, plummeted during the first months of the lockdown, and started rising again since the past few months. When testing for cointegration with the unemployment rate, we find that the discrepancy indicator exhibits a long- term relationship with unemployment in most countries, while the Knightian uncertainty indicator shows a purely short-run relationship. The impact of both indicators on unemployment is characterised by considerable asymmetries, showing a more intense reaction to decreases in the level of uncertainty. While this finding may seem counterintuitive at first sight, it somehow reflects the fact that during recessive periods, the level of disagreement in the employment expectations of consumers drops considerably.

JEL Classification: C14, C32, C82, C83, J01.

Keywords: COVID-19, Employment uncertainty, Unemployment expectations, Disagreement, Consumers, Cointegration.

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1. Introduction

The sharp contraction in economic activity triggered by the uncertainty caused by the pandemic has had a major impact in the labour market. In spite of the policy measures aimed at supporting workers, the shock on the labour market has been unprecedented, with the unemployment rate exhibiting a sharp increase between February and April 2020. Against this backdrop, the analysis of unemployment expectations and uncertainty seems more timely than ever before. Despite the existence of a huge and growing literature on the impact of economic uncertainty on activity (Baker et al. 2016; Carriero et al. 2018; Ghirelli et al. 2021; Škrabić Perić and Sorić 2018), its impact on unemployment has been somehow relegated to the background, in a similar way to unemployment expectations (Abberger 2007; Claveria 2019; Sorić et al. 2019). Some exceptions are the works of Caggiano et al. (2014, 2017), Choi and Loungani (2015), Netšunajev and Glass (2017) and Nodari (2014), which empirically confirm the contribution of economic uncertainty shocks to the volatility of unemployment, especially during recessions. Nevertheless, these studies focus on the impact of economic uncertainty but do not analyse the effect of employment uncertainty.

Due to the difficulty of measuring uncertainty, the impact of employment uncertainty shocks to unemployment has largely been overlooked. While some authors have analysed the relationship between oil price shocks and unemployment (Kocaasland 2019), or between exchange-rate uncertainty and unemployment (Chang 2011), to our knowledge there is just one previous study that analyses the impact of employment uncertainty on unemployment (Claveria 2021).

Therefore, in this study we intend to cover this deficit by measuring and assessing employment uncertainty in European countries. To this end, we use consumer survey expectations of future unemployment as input to calculate employment uncertainty. Survey-derived measures of expectations dispersion constitute a primary source to elicit perceived uncertainty of economic agents, as they present several advantages over alternative methods to proxy such an elusive notion as uncertainty. In this sense, Bloom et al. (2021) have recently used business expectations to measure business' subjective uncertainty.

On the one hand, and as opposed to measures based on realized volatility in equity markets (Basu and Bundick 2012; Bekaert et al. 2013) or in the conditional volatility of the unforecastable components of economic variables (Jurado et al. 2015; Meinen and

Roehe 2017; Rossi and Sekhposyan 2015), the forward-looking nature of expectations makes them particularly useful to compute survey-derived measures of expectations dispersion (Binding and Dibiasi 2017; Clements and Galvão 2017).

On the other hand, there is recent evidence that different dimensions of uncertainty have different effects on the economy (Henzel and Rengel 2017). Claveria (2020) has shown the suitability of addressing the analysis of each type of uncertainty independently, as the aggregation of expectations both from different agents and from different variables in order to approximate economic uncertainty may end up causing the effect of the different dimensions of uncertainty on activity to be compensated.

As a result, in this study we exclusively use consumers' unemployment expectations elicited from the consumer tendency survey conducted by the European Commission to compute two different measures of employment uncertainty. We use two alternative approaches recently proposed in the literature. First, we use an indicator that directly measures Knightian uncertainty (Dibiasi and Iselin, 2019). As suggested by the authors, uncertainty in the sense of Knight (1921) is defined by a situation in which agents are no longer able to form expectations about the future. Therefore, through the measurement of the proportion of respondents who explicitly state that they 'do not know' what the expected direction of their unemployment expectations is, we compute a first indicator of labour uncertainty.

Second, we compute a disagreement measure of consumer unemployment expectations. With this aim we apply the geometric approach proposed by Claveria et al. (2019). This method allows to compute a dimensionless metric that gives the proportion of discrepancy among survey respondents, where zero corresponds to the point of minimum disagreement, and one indicates that the answers are equidistributed among the different response categories.

The prospective nature of survey expectations, together with the availability of information regarding consumers' unemployment expectations has allowed us to focus on this overlooked aspect in such a critical moment as the present, a year after the irruption of the covid-19 pandemic. In the study we examine the evolution of consumers' perceived uncertainty about employment and its relation to that of the unemployment rate. To this aim, we make use of non-linear econometric techniques to test for cointegration between labour uncertainty and unemployment. This approach allows us to test for the existence of a long-term relationship between both variables in the main European economies.

The remainder of the paper is structured as follows. The next section presents the data and analyses the two proxies of employment uncertainty. Section 3 presents the methodology used to evaluate the long-term relationship between both metrics and the unemployment rate. Empirical results are presented in Section 4. Finally, Section 5 concludes.

2. Data

The European Commission conducts monthly business and consumer tendency surveys in which respondents are asked whether they expect different economic variables to rise, fall or remain unchanged. In the present study we focus on consumers' qualitative expectations about future unemployment. Specifically, we use the raw data from from 2005.M1 to 2020.M2 for 22 European economies, the EA and EU. The different countries have been denoted as follows: Belgium (BE), Czech Republic (CZ), Denmark (DK), Germany (DE), Estonia (EE), Greece (EL), Spain (ES), France (FR), Italy (IT), Latvia (LV), Lithuania (LT), Luxemburg (LU), Hungary (HU), the Netherlands (NL), Austria (AT), Poland (PL), Portugal (PT), Slovenia (SI), Slovakia (SK), Finland (FI), Sweden (SE), United Kingdom (UK), Euro Area (EA) and the European Union (EU). For the UK there is only available information up until 2020.M12.

In consumer tendency surveys, respondents are asked about their expectations about how the level of unemployment will change in their country over the next 12 months. Consumers are faced with six options: PP_t measures the percentage of respondents reporting a sharp increase in the variable, P_t a slight increase, E_t no change, M_t a slight fall, MM_t a sharp fall and, N_t don't know. Survey results are usually published as balances, which can be regarded as a diffusion index consisting of the subtraction between the aggregate percentages of response corresponding to the extreme categories. See Pinto et al. (2020) for a comprehensive analysis of diffusion indexes. For consumers, the balance is computed as follows:

$$B_t = \left(PP_t + \tfrac{1}{2}P_t\right) - \left(\tfrac{1}{2}M_t + MM_t\right) \qquad (1)$$

Seasonally-adjusted balances are published each month by the EC, but the series corresponding to each response category are only available in raw form, that is, the aggregate percentage of respondents in each category. Since both metrics of employment uncertainty are computed from raw data, which is not seasonally-adjusted, we have opted for a zero-phase low-pass filter to extract the periodicities of the survey responses that are closest to those observed in seasonally-adjusted unemployment rates. We have used a Butterworth filter, which is a type of signal processing filter designed to have a frequency response as flat as possible in the pass band (Butterworth, 1930). As a result, the Butterworth filter is also referred to as a maximally flat magnitude filter. See Claveria et al. (2021) for a justification of low-pass filtering for business and consumer survey expectations.

Many studies on economic uncertainty rely on quantitative macroeconomic expectations made by professional forecasters to compute dispersion-based proxies (Dovern 2015; Lahiri and Sheng 2010; Mankiw et al. 2004; Oinonen and Paloviita 2017). However, consumer tendency surveys provide qualitative measures of agents' expectations, and therefore measures of disagreement among survey respondents mainly use the dispersion of balances as a proxy for uncertainty (Bachmann et al. 2013; Girardi and Reuter 2017; Mokinski et al. 2015). This idea was first suggested by Theil (1955), who proposed using a disconformity coefficient. In their seminal paper, Bachmann et al. (2013) applied an indicator of disagreement based on the square root of the variance of the balance, which in the case of the consumers would be computed as follows:

$$DISP_t = \sqrt{\left(PP_t + \tfrac{1}{2}P_t\right) - \left(\tfrac{1}{2}M_t + MM_t\right) - (B_t)^2} \qquad (2)$$

The fact that expression (2) does not include the share of neutral responses (E_t) causes the level of disagreement to be overestimated, as shown by means of a simulation experiment in Claveria et al. (2019). Therefore in this study, we use the disagreement metric proposed by Claveria (2021), which incorporates the information coming from all the reply options. Based on the fact that the sum of the shares adds to one, and that the vector encompassing all shares of responses can be projected on to a simplex, the author proposed using the barycentre system to geometrically derive the ratio of agreement among respondents as the distance of the vector to the centre of the simplex divided by the distance from the centre to the nearest vertex. For simplicity, we add *P* and *PP*, *M* and *MM*, and *E* and *N* to reduce the number of response categories from 6 to 3. This way, an indicator of disagreement for a given period in time can be formalized as:

$$DIS_t = 1 - \left[\frac{\sqrt{\left(PP_t + P_t - \tfrac{1}{3}\right)^2 + \left(N_t + E_t - \tfrac{1}{3}\right)^2 + \left(MM_t + M_t - \tfrac{1}{3}\right)^2}}{\sqrt{\tfrac{2}{3}}} \right] \qquad (3)$$

One of the main advantages of this metric is that is bounded between zero and one, and therefore it is directly interpretable: being zero the point of minimum disagreement, where one category draws all the answers, and one the point of maximum disagreement in which answers are equidistributed among the three response categories.

When comparing the evolution of the geometric measure of disagreement (2) to that of the standard deviation of the balance (1) in several European countries, Claveria (2021) obtained a high positive correlation between both measures of disagreement, and found that the main difference between both measures mainly lied in their average level and dispersion, being *DISP* higher and more volatile.

As commented in the Introduction, Dibiasi and Iselin (2019) proposed using the share of respondents that, when surveyed, explicitly responded not knowing what the expected direction of their expectations was in order to obtain a direct measure of Knightian uncertainty. Hence, in this study we use the share of consumers that respond that they do not know the expected direction of their unemployment expectations (N_t), which represents captures the proportion of consumers that are not able to formalize expectations about the future unemployment level. See Dibiasi and Iselin (2019) for a comparison of (2) to Theil's disconformity coefficient and analysis of firms' direct perception of investment uncertainty. For the sake of comparability, we normalise N_t.

As mentioned before, both metrics of employment uncertainty are computed from raw data, which is not seasonally-adjusted. In order to obtain a less noisy signal, we have used a Butterworth filter in order to extract the periodicities that are closest to those observed in seasonally-adjusted unemployment rates.

In Table 1 we present the summary statistics of the proxies of employment uncertainty: disagreement in consumer unemployment expectations (*DIS*) and the normalised proportion of consumers who explicitly manifest that they do not know how the level of unemployment will change in their country over the next 12 months (*N*).

On the one hand, results in Table 1 show that overall, the proportion of disagreement tends to be high, well above 50% in all countries except Greece and Portugal. On the other hand, the dispersion of *N* tends to be higher than that of *DIS* in most countries. Both metrics covary during the sample period, showing a significant correlation in all cases except in Denmark, Estonia and Spain, where both indicators of uncertainty seem to evolve independently.

This notion is further confirmed in Figure 1 where we compare the evolution of both proxies of employment uncertainty. The graphs show a high concordance between both indicators, especially at the inflection points, corresponding to periods of extreme uncertainty such as the 2008 crisis or the current one. In Section 4, we test for cointegration between both measures and unemployment, confirming the assessed long-term relationship between *DIS* and unemployment in most cases.

Table 1
Descriptive and correlation analysis – Disagreement (DIS) and Uncertainty (N)

Country	DIS		N		
	mean	std. dev.	mean	std. dev.	correl.
Belgium	0.650	0.234	0.370	0.256	0.160*
Czechia	0.674	0.168	0.291	0.205	0.163*
Denmark	0.759	0.120	0.394	0.207	-0.005
Germany	0.666	0.159	0.370	0.167	0.322**
Estonia	0.667	0.148	0.362	0.231	0.010
Greece	0.428	0.233	0.212	0.174	0.447***
Spain	0.677	0.199	0.243	0.249	0.089
France	0.597	0.220	0.270	0.149	0.576**
Italy	0.621	0.161	0.246	0.198	-0.187**
Latvia	0.652	0.147	0.474	0.207	0.473**
Lithuania	0.661	0.195	0.386	0.218	0.421**
Luxemburg	0.559	0.195	0.371	0.175	0.558**
Hungary	0.548	0.152	0.363	0.141	0.586**
Netherlands	0.635	0.235	0.370	0.221	0.520**
Austria	0.652	0.195	0.345	0.192	0.115*
Poland	0.581	0.097	0.419	0.172	0.146*
Portugal	0.484	0.289	0.335	0.223	0.686**
Slovenia	0.618	0.228	0.273	0.214	0.238**
Slovakia	0.682	0.195	0.342	0.218	0.271**
Finland	0.723	0.162	0.283	0.166	0.328**
Sweden	0.727	0.155	0.257	0.221	0.193**
UK	0.629	0.201	0.406	0.255	0.624**
EA	0.689	0.177	0.373	0.221	0.554**
EU	0.693	0.171	0.425	0.220	0.660**

Notes: std. dev. denotes standard deviation and correl. the linear coefficient of correlation.. DIS refers to disagreement regarding consumers' 'unemployment expectations over the next 12 months' and N refers to the normalised share of consumers' that choose the 'I do not know' category in the consumer survey. UK denotes the United Kingdom, EA the Euro Area, and EU the European Union. ** Correlation significant at the 0.01 (2-tailed), * at the 0.05 level.

Fig. 1a. Evolution of DIS vs N

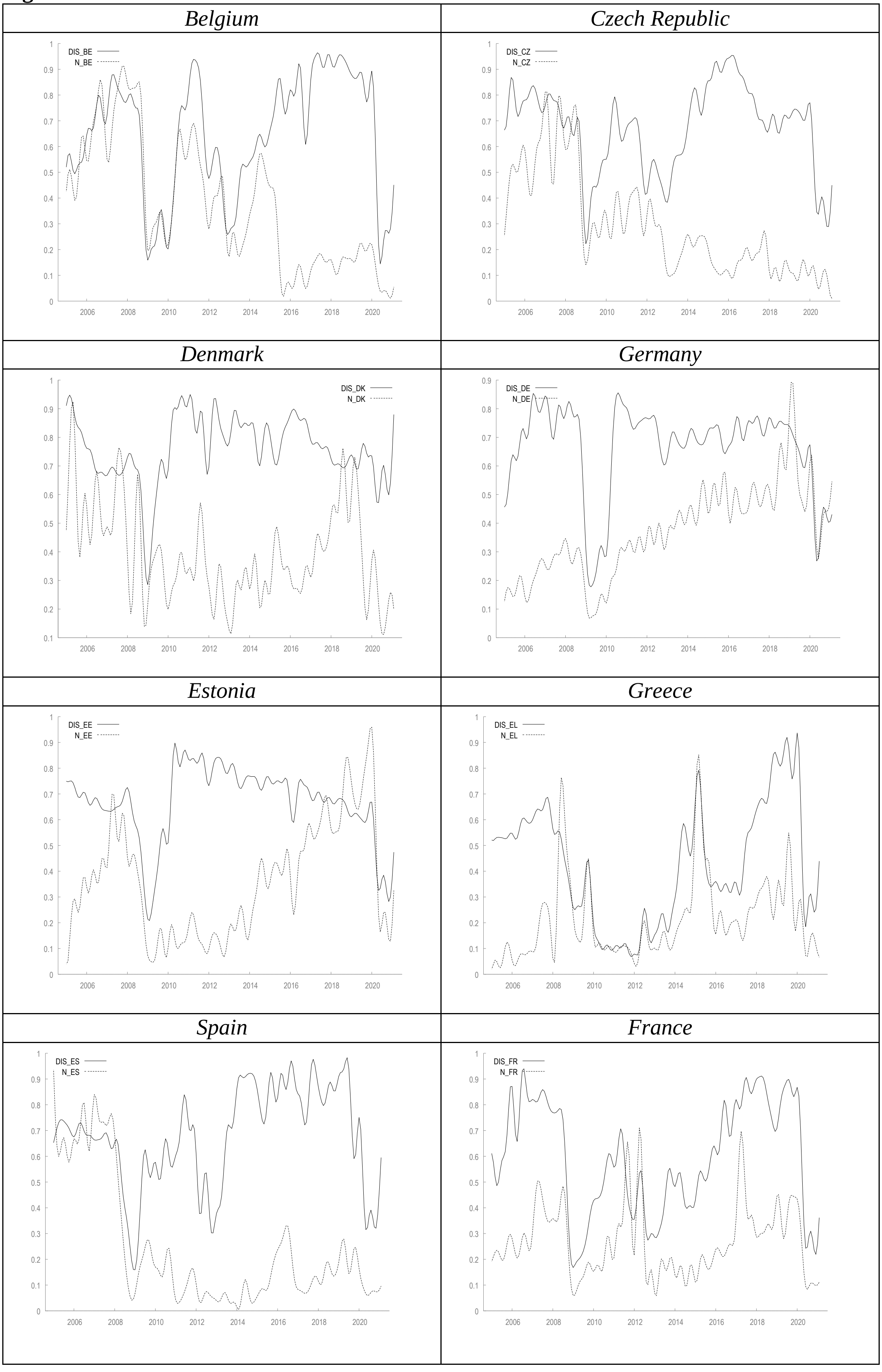
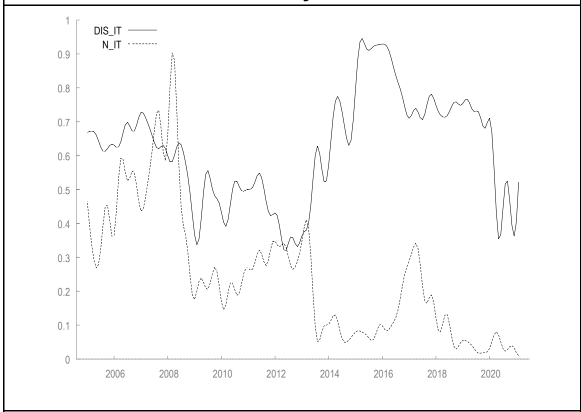


Fig. 1b. Evolution of industry, service, retail trade and construction disagreement

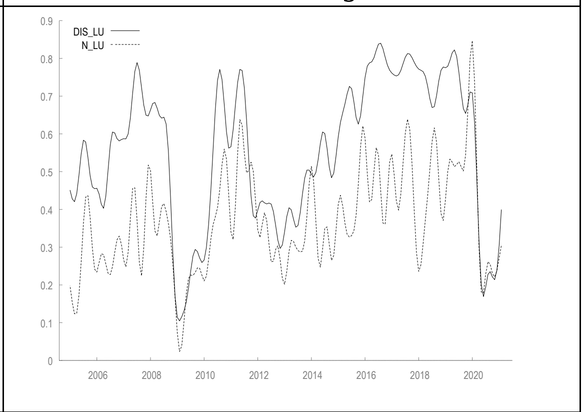
Italy



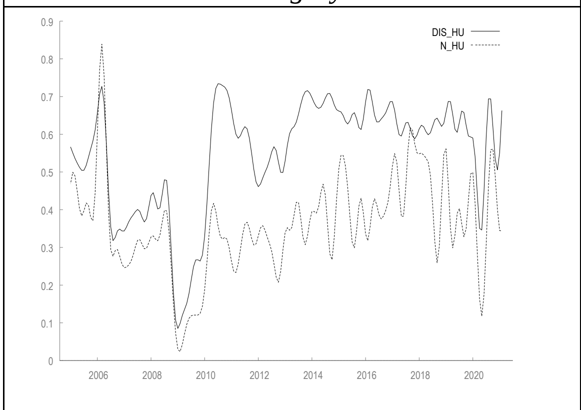
Latvia

Lithuania

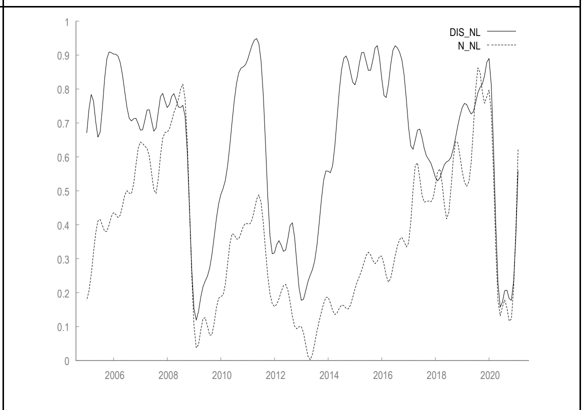
Luxemburg



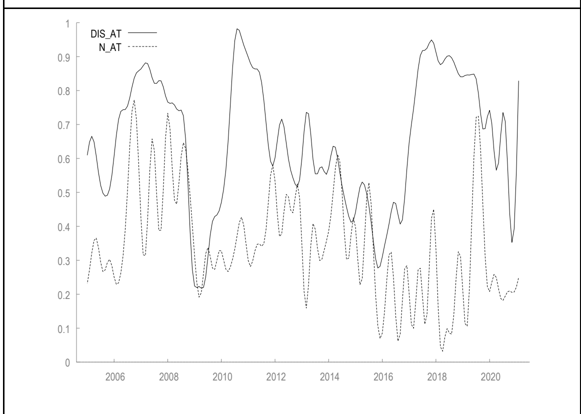
Hungary



Netherlands



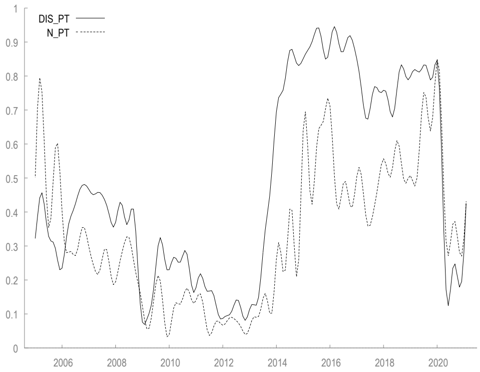
Austria



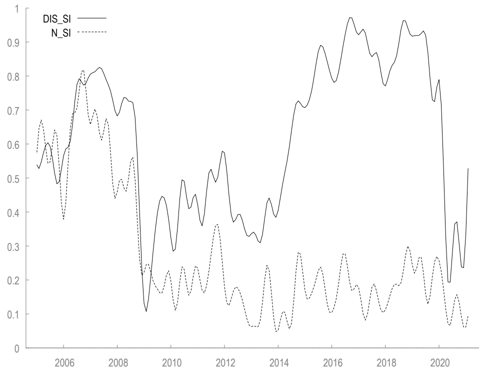
Poland

Fig. 1c. Evolution of industry, service, retail trade and construction disagreement

Portugal



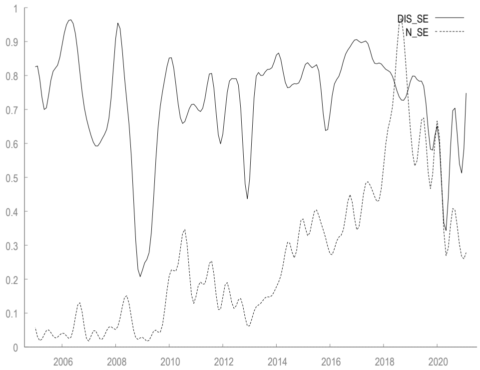
Slovenia



Slovakia

Finland

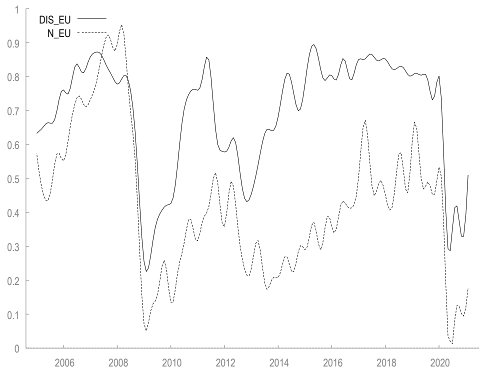
Sweden



United Kingdom

Euro Area

European Union



Notes: *DIS*_country represents the evolution of disagreement regarding consumers' 'unemployment expectations over the next 12 months'; *N*_country refers to the normalised share of consumers' that choose the 'I do not know' category in the consumer survey. Both series have been smoothed by means of the Butterworth filter.

3. Methodology

In this section we present the methodology used to test for the existence of a long-term relationship between unemployment uncertainty and the unemployment rate, henceforth denoted as UN. Our estimation strategy is largely conditioned by the fact that the assessed dataset is consisted of a mixture of I(0) and I(1) time series.[1] This prevented us from framing the study within a standard Johansen cointegration or VAR analysis, and stimulated us to utilize an AutoRegressive Distributed Lag (ARDL) model. The proposed ARDL methodology has some noteworthy benefits. It allows for a combination of I(0) and I(1) variables (Pesaran et al. 2001), but it also preserves valuable degrees of freedom by allowing for different lag orders for each variable at hand. Additionally, it allows us to augment the model in a nonlinear fashion. Namely, previous studies of economic uncertainty have unequivocally demonstrated its asymmetric impact on aggregate economic activity (Jones and Enders 2016; Caggiano et al. 2017, 2021; Jackson et al. 2020), finding a stronger effect for uncertainty increases than for its decreases. To that end, we employ the non-linear ARDL (NARDL) framework of Shin et al. (2014):

$$\begin{aligned} \Delta UN_t = a_0 + \rho UN_{t-1} + \theta^+ X_{t-1}^+ + \theta^- X_{t-1}^- + \\ \sum_{j=1}^{p-1} a_j \Delta UN_{t-j} + \sum_{j=0}^{q^+-1} \pi_{1,j}^+ \Delta X_{t-j}^+ + \sum_{j=0}^{q^--1} \pi_{1,j}^- \Delta X_{t-j}^- + e_t, \end{aligned} \tag{4}$$

where $X = \begin{cases} DIS \\ N \end{cases}$, $X_t^+ = \sum_{j=1}^{t} max(\Delta x_j, 0)$ and $X_t^- = \sum_{j=1}^{t} min(\Delta x_j, 0)$. Model (4) was estimated for each country in the sample and for each of the two uncertainty proxies (*DIS* and *N*). The optimal lag order of the NARDL model (p, q^+, and q^-) was determined via the general-to-specific approach (Greenwood-Nimmo and Shin 2013; Greenwood-Nimmo et al. 2013, 2013b; Shin et al. 2014). Model (4) was estimated in a step-wise fashion, starting from $p = q^+ = q^- = 6$ and then iteratively dropping all insignificant regressors with a 5% significance stopping rule. The null hypothesis of no cointegration ($\boldsymbol{H_0}$: $\rho = \theta^+ = \theta^- = 0$) is tested by a standard Wald test.

A novelty of NARDL in comparison to linear ARDL is the necessity to test for long-run (LR) symmetry ($\boldsymbol{H_0}$: $\theta^+ = \theta^-$) and short-run (SR) symmetry ($\sum_{j=0}^{q^+-1} \pi_{1,j}^+ = \sum_{j=0}^{q^--1} \pi_{1,j}^-$), again by means of a Wald test.

[1] Results obtained through the Augmented Dickey-Fuller unit root test are available upon request.

Greenwood-Nimmo et al. (2013) suggest to test for both types of (a)symmetries (LR and SR), and then to re-estimate equation (4) if only one type of asymmetry (or none) is found. This should prevent the researcher from obtaining biased results due to model misspecifications. If the null hypothesis of LR symmetry cannot be rejected, we therefore re-estimate equation (4) as:

$$\begin{gathered}\Delta UN_t = a_0 + \rho UN_{t-1} + \theta X_{t-1} + \\ + \sum_{j=1}^{p-1} a_j \Delta UN_{t-j} + \sum_{j=0}^{q^+-1} \pi_{1,j}^{+} \Delta X_{t-j}^{+} \quad + \sum_{j=0}^{q^--1} \pi_{1,j}^{-} \Delta X_{t-j}^{-} \quad + e_t,\end{gathered} \tag{5}$$

Similarly, in case the SR symmetry cannot be rejected, we re-estimate the model as:

$$\begin{gathered}\Delta UN_t = a_0 + \rho UN_{t-1} + \theta^{+} X_{t-1}{}^{+} + \theta^{-} X_{t-1}{}^{-} + \\ \sum_{j=1}^{p-1} a_j \Delta UN_{t-j} + \sum_{j=0}^{q-1} \pi_{1,j} \Delta X_{t-j} + e_t,\end{gathered} \tag{6}$$

Finally, if both types of symmetries cannot be rejected, we estimate the purely linear ARDL model:

$$\Delta UN_t = a_0 + \rho UN_{t-1} + \theta X_{t-1} + \sum_{j=1}^{p-1} a_j \Delta UN_{t-j} + \sum_{j=0}^{q-1} \pi_{1,j} \Delta X_{t-j} + e_t, \tag{7}$$

Upon estimating a separate NARDL model for each country, two diagnostic tests are carried out for each NARDL model: a Ljung-Box test for autocorrelation of 12$^{\text{th}}$ order, and an Engle's Autoregressive Conditional Heteroscedasticity (ARCH) test of 12$^{\text{th}}$ order.

Whenever the residuals turned out to be characterised by autocorrelation or heteroscedasticity at the 5% significance level, the Newey-West autocorrelation- and heteroscedasticity-consistent (HAC) estimator is utilised.

As the final step of our empirical strategy, conditional on the presence of significant asymmetries (SR, LR, or both), we estimate the dynamic multipliers, i.e. responses of unemployment to positive and negative unit changes in uncertainty ($X_t^{+}$and X_t^{-}):

$$m_h^{+} = \sum_{j=0}^{h} \frac{\partial UN_{t+j}}{\partial X_t^{+}} \text{ and } m_h^{-} \sum_{j=0}^{h} \frac{\partial UN_{t+j}}{\partial X_t^{-}},\ h = 0, 1, 2, \ldots \tag{8}$$

This allows us to empirically test whether unemployment indeed reacts asymmetrically to survey-based uncertainty measures.

4. Empirical analysis

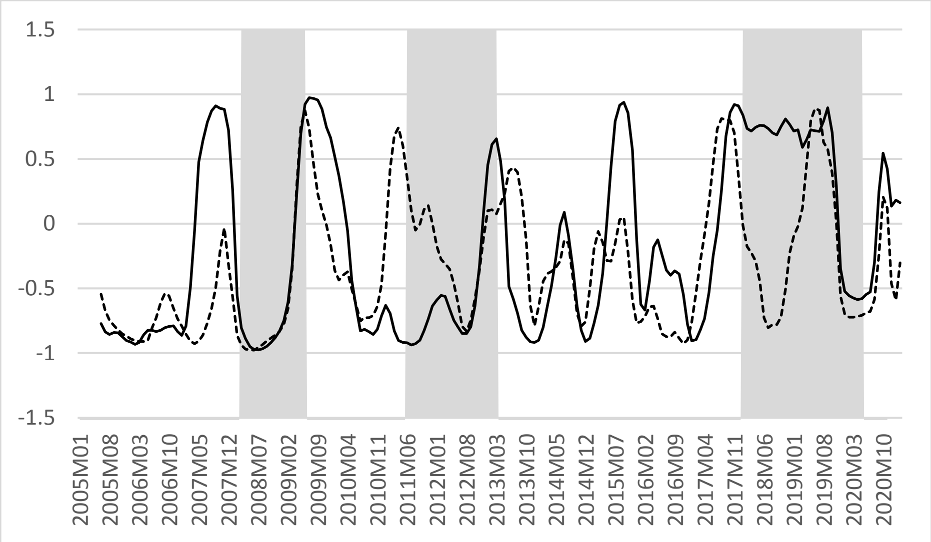
In this section, we present the empirical results of the NARDL cointegration analysis. Table 2 summarises the results for the impact of *DIS* on the unemployment rate, while Table 3 presents analogous results for the relationship between *N* and unemployment. Instead of presenting the obtained parameters for each individual lag of each of the variables included in the models, we summarised the main findings by presenting only the nature of the final model specification, i.e. whether there are significant asymmetries in the model, the F statistics associated to the cointegration tests, and the long-run uncertainty parameters.

Table 2 suggests that employment uncertainty approximated via disagreement (*DIS*) is cointegrated with unemployment in all countries except France, Italy, Luxembourg, and the UK. The estimated long-run coefficients are negative in all countries with a significant long-term relationship, implying that a rise in disagreement is associated with a decrease in the unemployment rate. While this result may seem counterintuitive at first, there may be a plausible explanation.

Economic agents' forecasting disagreement is often regarded as a proxy for economic uncertainty (Bachmann et al. 2013). Bloom (2014) established counter cyclicality as one of the fundamental stylised facts of economic uncertainty. On the one hand, the obtained results could be somehow indicating that highly heterogeneous survey responses regarding unemployment expectations do not necessarily indicate high employment uncertainty. This notion is also in line with recent evidence indicating that forecast disagreement and news-based indicators of uncertainty capture inherently different phenomena (Glas 2020; Krüger and Nolte 2016; Rich and Tracy 2021; Sorić and Lolić 2017). Regardless of that, the computed measure of disagreement indeed includes valuable information for the long-run state of unemployment, and this finding is very robust across countries.

On the other hand, the obtained results may be also reflecting the fact that during periods of severe recession such as the current one, consumers' expectations in relation to employment become more uniform, aligning around a pessimistic perspective. In this sense, to further scrutinise the potential reasons for a negative relationship between the assessed uncertainty measures and unemployment, we calculate the 12-month rolling window correlation between the two stated series. The obtained results for the EA are presented in Figure 2, along with the shaded areas corresponding to recessions.

Figure 2. Rolling-window correlation of uncertainty measures and unemployment for the EA



Notes: Solid line represents the correlation between *DIS* and the unemployment rate in the EA. Dashed line represents the correlation between *D* and the unemployment rate in the EA. Shaded areas correspond to recessions (source: Federal Reserve Economic Data).

As it can be seen in Figure 2, the correlation between uncertainty and unemployment plummets into negative territory in recessions. It seems that once the economic outlook reaches its trough, uncertainty levels also drop (see Figure 1) as agents' expectations of the immediate future look so pessimistic that there is hardly any uncertainty regarding the direction of unemployment. This pattern repeats quite regularly in recessions. It is observed in the 2008 crisis, just as in the European sovereign debt crisis, and the recent pandemic-caused turbulences. As the real economy goes in the expected downfall, agents are almost unified in the belief that the situation will worsen (generating low disagreement), and at the same time unemployment actually rises, this combination of effects ultimately yields a negative relationship between uncertainty and unemployment during recessions, which obviously conditions the overall negative long-run relationship between the two variables.

Our estimates are in line with previous literature. Chang (2011) analysed the relationship between exchange-rate uncertainty and unemployment for South Korea and Taiwan, obtaining a long-run equilibrium relationship. Hayford (2000) used the variance of the unemployment forecasts of the Livingston survey to proxy unemployment uncertainty and analysed its effect on economic activity, finding that it was Granger caused by inflation. These findings are in line with theoretical macroeconomic models, indicating the interconnections between different types of uncertainty (Henzel and Rengel 2017; Sánchez 2012).

In a recent article, Claveria (2021) also used unemployment expectations from consumers surveys to proxy unemployment uncertainty. The author found that shocks in unemployment uncertainty were found to lead to a decrease in unemployment rates, but that they were of smaller magnitude than those of economic uncertainty or of inflation uncertainty.

As the relationship between uncertainty and unemployment is obviously dependent on the business cycle, this type of behaviour brings our attention to the possible asymmetries in the observed relationship. It may be the case that unemployment generally reacts differently to increases and decreases in uncertainty. Table 2 reveals that there are quite a few asymmetries between *DIS* and unemployment in their cointegration equations, but the SR analysis is often asymmetric. On the other hand, the results obtained for *N* and UN are quite different (see Table 3). The LR relationship between these two variables is mostly not significant, but there are many asymmetric SR relationships. To shed additional light on the asymmetry issue, we calculate the dynamic multipliers, as presented in Figure 3 and Figure 4. The dynamic multipliers are presented for each model with a significant SR and/or LR asymmetry, according to Wald test result.

The graphical presentations given in Figure 3 reveal that unemployment mostly rises in response to uncertainty increases, and the other way around. In this sense, we want to note that we proxy employment uncertainty using consumers' disagreement regarding their unemployment expectations. Our data suggests that agents generate the most homogeneous expectations during extreme events such as recessions. Due to such behaviour, a fall in forecasting disagreement corresponds to an increase of actual unemployment.

When it comes to the dynamic multipliers of UN in response to *N* (Figure 4), the results are somewhat similar. Again, for a vast majority of countries with significant asymmetries (95% asymmetry confidence interval not including zero), unemployment seems to react more intensively to decreases in Knightian uncertainty. Again, the share of consumers unable to formalize expectations about unemployment considerably falls in economic downturns (see Figure 1). This finding drives the negative sign of uncertainty parameters in most specifications in Table 3, although the observed variables mostly do not form a significant cointegrating equation.

Although there are not many studies focused on the asymmetries in the impact of unemployment uncertainty, our findings are in line with the scarce previous research on this topic. Kocaasland (2019) also found that unemployment rates reacted asymmetrically to positive and negative shocks on oil price uncertainty.

Table 2
NARDL cointegration analysis results – Effect of *DIS* on unemployment

Country	Type of asymmetry	Cointegration test F value	θ^{+}	θ^{-}
Belgium	-	15.62**	-0.0585**	
Czechia	SR	12.35**	-0.0806**	
Denmark	SR	20.03**	-0.2285**	
Germany	SR ^{HAC}	15.89**	-0.0065	
Estonia	-	18.99**	-0.1116**	
Greece	-	9.37**	-0.3290**	
Spain	-	5.91**	-0.0212**	
France	SR ^{HAC}	5.42	-0.0718**	
Italy	-	3.87	-0.0519**	
Latvia	SR ^{HAC}	13.88**	-0.0623**	
Lithuania	SR	6.23*	-0.0230**	
Luxemburg	LR	2.00	0.0006	-0.0096
Hungary	-	9.65**	-1.0758**	
Netherlands	LR	14.07**	-0.0502**	
Austria	(SR, LR) ^{HAC}	12.92**	-0.1109**	-0.1205**
Poland	LR^{HAC}	6.91*	-0.0172**	-0.0420**
Portugal	-	14.42**	-0.0244**	
Slovenia	SR ^{HAC}	7.39**	-0.0347**	
Slovakia	-	6.49*	-0.0220**	
Finland	-	10.49**	-0.1902**	
Sweden	SR, LR	18.72**	-0.2699**	-0.2868**
UK	SR, LR	4.98	-0.0832**	-0.0708**
EA	-	71.15**	-0.0687**	
EU	-	24.77**	-0.0547**	

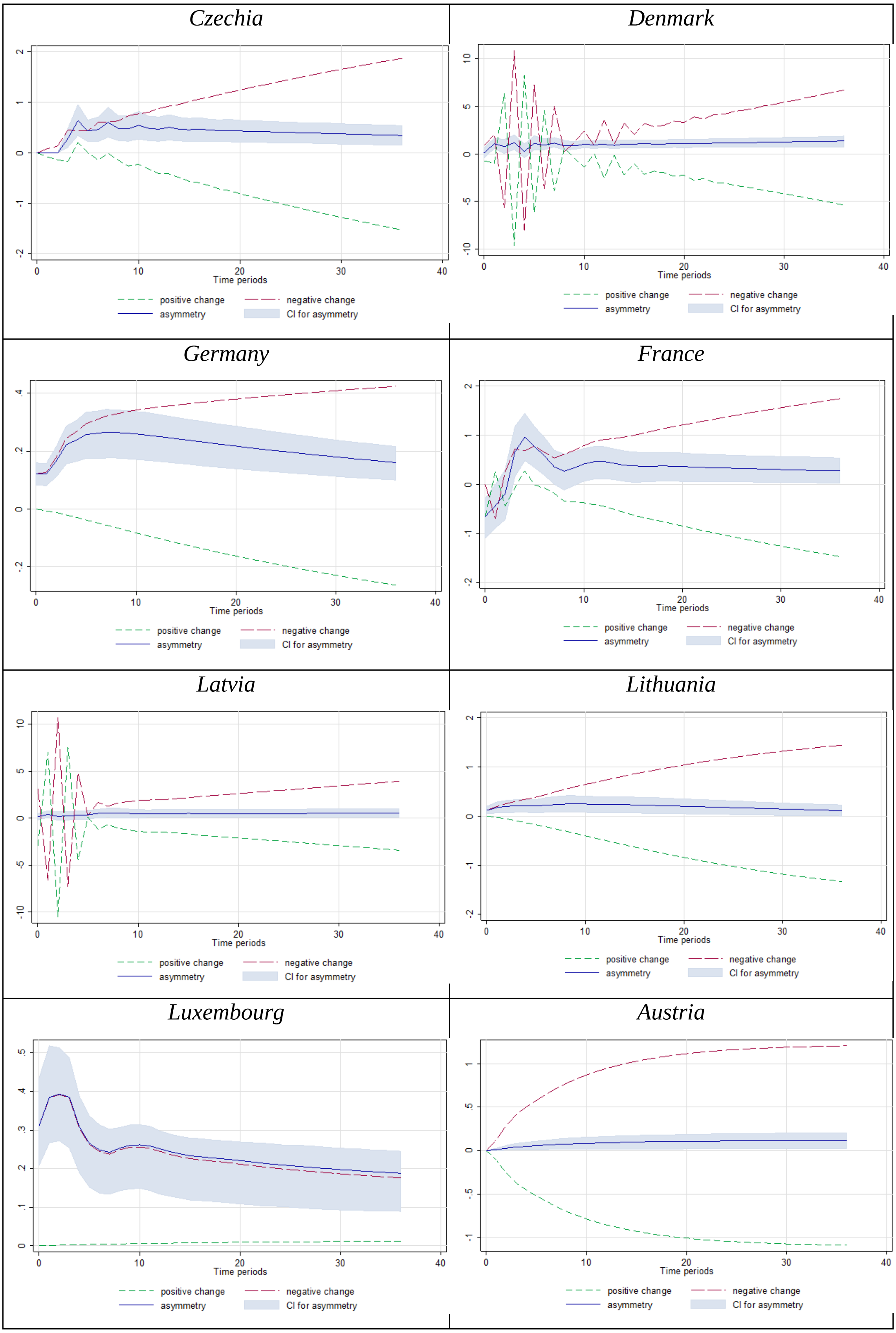
Notes: ** Significance at the 0.01 level, * at the 0.05 level. ^{HAC} denotes a model estimated using the Newey-West standard error correction due to autocorrelation and/or heteroscedasticity issues. Full set of results is available upon request.

Table 3
NARDL cointegration analysis results – Effect of *N* on unemployment

Country	Type of asymmetry	Cointegration test F value	θ^{+}	θ^{-}
Belgium	SR	0.55	-0.0041	
Czechia	SR	2.03	-0.0203	
Denmark	none ^{HAC}	5.55	-0.0509**	
Germany	none	9.66**	-0.0064	
Estonia	SR ^{HAC}	3.48	-0.0313*	
Greece	none ^{HAC}	1.97	-0.0212	
Spain	(SR, LR) ^{HAC}	2.80	-0.0233*	-0.0188*
France	SR ^{HAC}	3.82	-0.1596**	
Italy	none ^{HAC}	0.79	-0.0067	
Latvia	SR ^{HAC}	5.22	-0.0182*	
Lithuania	none	3.89	-0.0010	
Luxemburg	(SR, LR) ^{HAC}	1.27	-0.0004	-0.0036
Hungary	(SR & LR) ^{HAC}	5.60	-0.0961**	-0.0888**
Netherlands	SR ^{HAC}	6.35*	-0.0437**	
Austria	none ^{HAC}	1.59	0.0306	
Poland	none ^{HAC}	4.79	-0.0063	-0.0043
Portugal	SR	6.47*	-0.0266**	
Slovenia	LR	6.66*	-0.0834**	-0.0684**
Slovakia	SR ^{HAC}	6.77*	-0.0290**	
Finland	LR	12.51**	-0.5119**	-0.5259**
Sweden	LR ^{HAC}	5.43	-0.1301**	-0.1820**
UK	none	20.39**	-0.0834***	
EA	none ^{HAC}	2.11	-0.0057	
EU	SR	0.14	-0.0020	

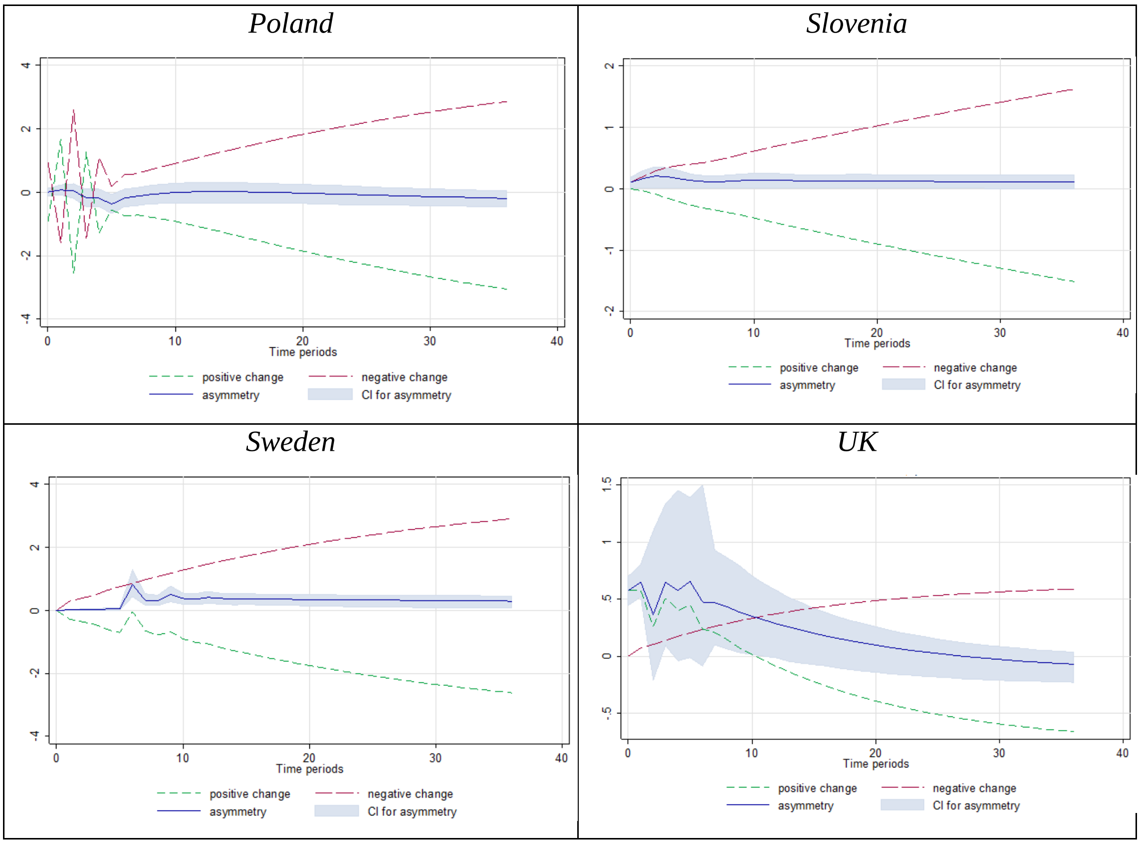
Notes: ** Significance at the 0.01 level, * at the 0.05 level. ^{HAC} denotes a model estimated using the Newey-West standard error correction due to autocorrelation and/or heteroscedasticity issues. Full set of results is available upon request.

Figure 3. Estimated dynamic multipliers – Effect of *DIS* on unemployment



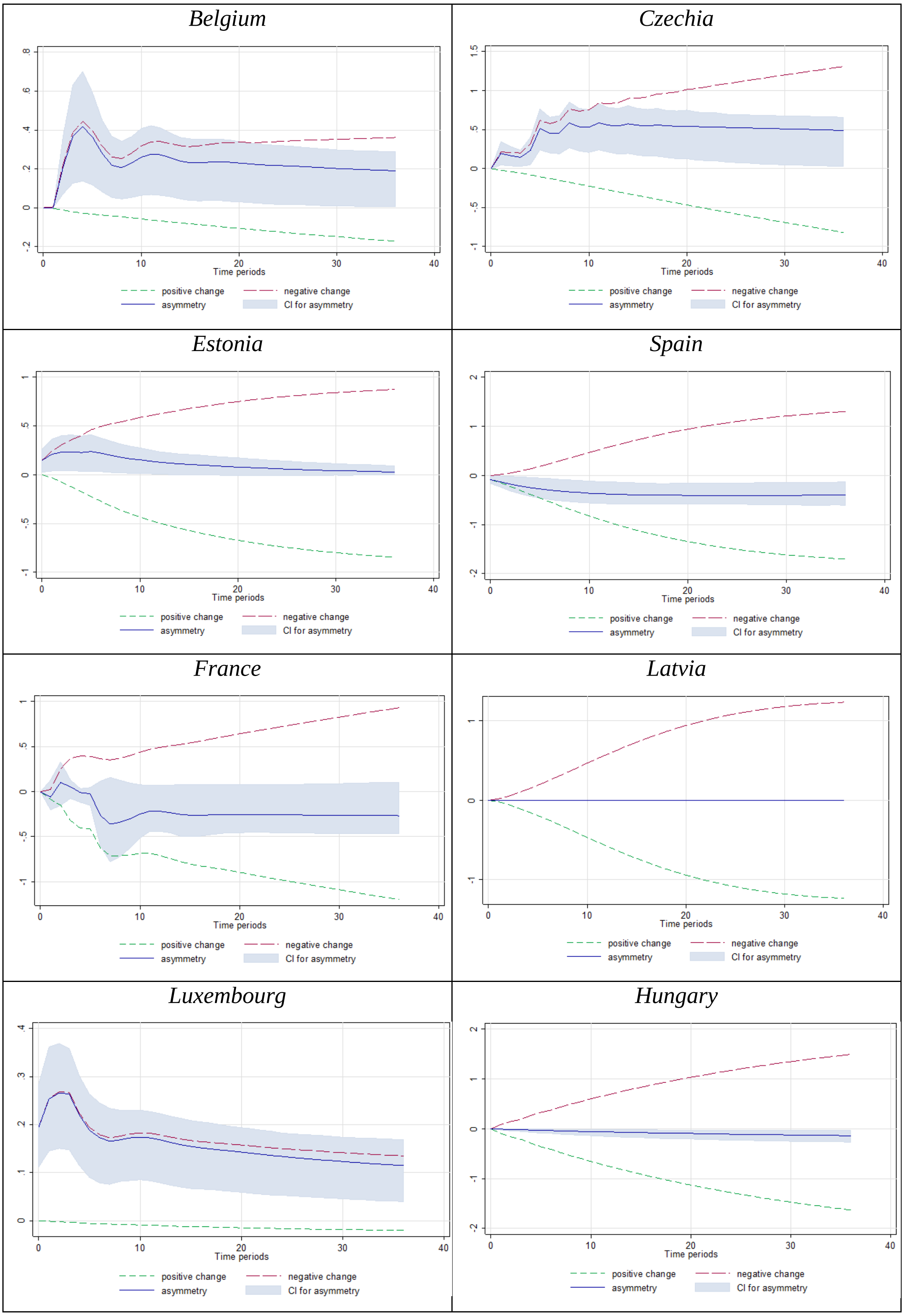
Note: Shaded area corresponds to the 95% confidence interval (CI) for asymmetry (difference between positive and negative effect).

Figure 3 (cont.). Estimated dynamic multipliers – Effect of *DIS* on unemployment



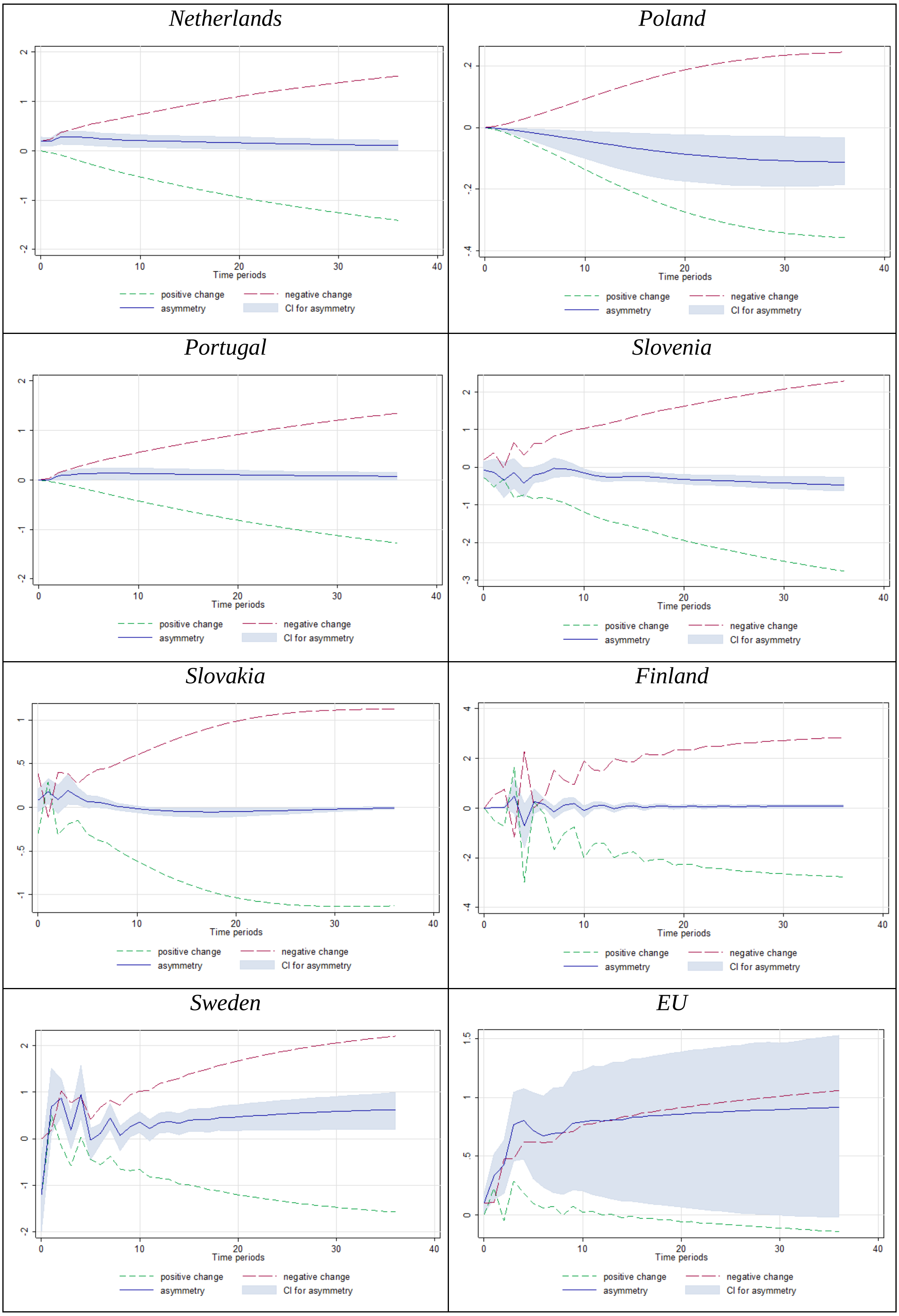
Note: Shaded area corresponds to the 95% confidence interval (CI) for asymmetry (difference between positive and negative effect).

Figure 4. Estimated dynamic multipliers – Effect of *N* on unemployment



Note: Shaded area corresponds to the 95% confidence interval (CI) for asymmetry (difference between positive and negative effect).

Figure 4 (cont.). Estimated dynamic multipliers – Effect of *N* on unemployment



Note: Shaded area corresponds to the 95% confidence interval (CI) for asymmetry (difference between positive and negative effect).

5. Concluding remarks

While the analysis of economic uncertainty is gaining renewed interest since the advent of the coronavirus pandemic and the subsequent economic disruption caused by the lockdown, the evaluation of employment dimension of uncertainty has typically been neglected. This omission has led us to focus on the measurement of employment uncertainty and its effect on unemployment. To this end we have made exclusive use of consumers' unemployment expectations elicited from tendency surveys, in which agents are asked about the expected direction of different economic variables. Using the different shares of responses (increase, decrease, no change) as the sole input, we computed a disagreement metric and compared it to a direct indicator of Knightian unemployment uncertainty, which is computed as the share of consumers who are not able to formalise expectations about future unemployment.

By isolating the 'employment' dimension of uncertainty and focusing exclusively on consumers expectations, we were able to compute two proxies of employment uncertainty and to isolate its effect on unemployment. We used cointegration analysis to evaluate the existence of a long-term relationship between both variables, and found that the disagreement indicator was cointegrated with unemployment in most of the countries. On the other hand, the measure of Knightian uncertainty only exhibited a long-term relationship in a few cases. Both assessed indicators showed considerable asymmetries in their effect on unemployment. The unemployment rate reacted more intensively to a decrease in both uncertainty proxies. Although this might seem unusual at first glance, our analysis revealed that employment uncertainty measured via disagreement substantially decreases during recessions, i.e. agents become more homogeneous in expecting rising unemployment. And that is indeed what may be explaining the negative impact of consumers' disagreement on unemployment.

The study sheds some light on this overlooked aspect in such a critical moment as the present, a year after the irruption of the covid-19 pandemic, when European economies are implementing damage contention measures aimed at supporting workers and at mitigating the unprecedented shock on economic activity. Notwithstanding, the study is not without limitations. Above all, we want to note that the findings of this research may be conditioned by several biases derived from the exogenous measurement of employment uncertainty. While the main aim of the research was to compare both proxies of uncertainty and their effects on unemployment, an important issue left for further research is the application of alternative approaches to approximate employment uncertainty such as the estimation of the unforecastable components of the unemployment rate. The analysis could also be extended to other tendency surveys, such as the industry survey, the service survey or the retail trade survey. Following the most commonly used methodological framework for this type of analyses, other lines of future research include the application of new developments in VAR analysis.

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