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"Economic uncertainty and suicide mortality in post-pandemic England"

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Abstract

This paper examines the relationship between different dimensions of economic uncertainty and suicide rates in England from 1985 to 2020, both in the short and long term. The study employs a non-linear autoregressive distributed lag framework for cointegration estimation. This approach allows testing for the existence of possible asymmetries in the response of suicide mortality to increased economic uncertainty. Uncertainty is gauged by different proxies that allow computing financial uncertainty and labour market uncertainty indicators. The analysis is replicated by gender and across regions, controlling for unemployment and economic growth. Overall, the analysis suggests that uncertainty intensified during the first year of the COVID-19 pandemic. This is in line with the stylized facts of economic uncertainty and its pronounced role in recessions. When replicating the experiment by gender, we find that women seem to be more sensitive to changes in uncertainty. Regarding the existence of asymmetries, we found that decreases in economic uncertainty have a greater impact on suicide mortality than increases.

JEL Classification: C12; C32; I15; J17; Z18.

Keywords: Mental health; Suicide; Economic Uncertainty; Prevention; Time series analysis.

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Highlights

- Examination of the long-run relationship between uncertainty and suicide in England
- Assessment of the effect of political, financial and labour market uncertainty indicators
- Use of non-linear autoregressive distributed lag approach to cointegration estimation
- Test for long-run and short-run potential asymmetries by gender and across regions
- Impact of decreases in economic uncertainty is greater than that of increases
- Gender differences in the response to changes in economic uncertainty

1. Introduction

As noted by to the World Health Organization (WHO), mental and neurological disorders are highly prevalent, and account for a large burden of disease and disability globally (WHO, 2016). Social awareness of mental health problems has increased in recent years. In this sense, the pandemic seems to have acted as a catalyst for an often-overlooked issue. The implications of mental health problems have ramifications in all areas of society. On the one hand, mental health problems are one of the leading causes of disability worldwide. In a study performed by Oxford Economics (2016), the 2015 gross domestic product (GDP) in the United Kingdom (UK) was estimated to be £25 billion lower than expected due to economic consequences of mental health problems. Davies (2013) estimated the costs of mental health problems to the UK economy to be £70–100 billion per year (4.5% of the GDP). Similarly, a study by the Centre for Mental Health (2010) estimated the total costs of mental health problems in England alone were £105.2 billion per year. These estimates of the impact of mental health problems on economic activity testify to the importance of addressing mental health problems both socially and institutionally.

On the other hand, the link between mental health problems and suicide has been contrasted in different studies (Baeza et al., 2022; Mann et al., 2005; Qin et al., 2003). Amongst 20 to 29-year-olds, mental health problems are a major contributor to the burden of suicide (Yoshioka et al., 2022; Whiteford et al., 2013). Despite a progressive decline up until the Great Recession of 2008, suicide continues to be one of the most important causes of mortality in the UK. There is recent evidence that the COVID-19 pandemic has increased the incidence of mental health problems and suicidal ideations, suicide attempts and self-harm (Dubé et al., 2021; Farooq et al., 2021). Despite rising rates in mental health symptoms and suicidal ideation, it is still not yet clear to what extent this can end up translating into an increase in suicide rates (Kim, 2022). While Pirkis et al. (2022) and Sinyor et al. (2021) have found no evidence of increase in suicide during the initial months of the pandemic, Sánchez (2022) found that in 19 large counties of the United States (US) the total number of suicides per month was increasing during the first wave of COVID-19, analogously to what was found by Arya et al. (2022) and Yoshioka et al. (2022) in India and Japan respectively.

The link between mental health problems and suicide is often compounded by financial difficulties (Choi et al., 2019; Kim et al., 2014; Raschke et al., 2022). As a result, periods that coincide with financial crises are especially sensitive. It has been well documented that one of the factors contributing to higher incidence of mental health problems and suicide rates are economic crises (Koo and Cox, 2008; Kentikelenis et al., 2011; Marazziti et al., 2021; Phillips and Nugent, 2014; WHO, 2011). In a recent review of thirty-five studies from 2009 to 2019, Volkos and Symvoulakis (2021) found that specific social groups are more vulnerable during periods of economic crisis in terms of mental health impact. In this regard, recent works by Gunnell et al. (2020) and Kawohl and Nordt (2021) have pointed out that mental health effects of the pandemic may increase over time due to prolonged economic stress and underemployment. The difficulty in approximating an unobservable phenomenon such as economic distress has meant that this aspect has not been extensively analysed (Abdou et al., 2020). Recent advances in the measurement of economic uncertainty (Bachmann et al., 2013; Baker et al., 2016; Jurado et al., 2016) have given rise to a series of studies focused on the impacts of economic uncertainty shocks. However, until now very few studies have investigated the relationship between economic uncertainty and suicide rates (Abdou et al., 2020, 2022; Antonakakis and Gupta, 2017; Claveria, 2022; de Bruin et al., 2020; Vandoros et al., 2019; Vandoros and Kawachi, 2021).

In all the studies the authors found a significant association between economic uncertainty and suicide. Notwithstanding, most of these studies are focused in the US (Abdou et al., 2020, 2022; Antonakakis and Gupta, 2017; Vandoros and Kawachi, 2021), being the only exceptions the studies by Vandoros et al. (2019), who used daily data for England and Wales, and the studies by de Bruin et al. (2019) and Claveria (2022), who analysed suicide rates in 17 and 183 different countries, respectively.

Another common feature between these studies is the use of the indicator proposed by Baker et al. (2016), the Economic Policy Uncertainty (EPU) index. The only exceptions being Abdou et al. (2020) and Claveria (2022). In order to proxy economic insecurity, Abdou et al. (2020) used a stock market volatility index based on the S&P500 index options prices, the Chicago Board Options Exchange's Market Volatility Index (VIX), also referred to as the "investor fear gauge" (Whaley, 2000). This index reflects the market's expectations of future volatility.

Claveria (2022) computed the yearly average of the global economic policy uncertainty (GEPU) index proposed by Davis (2016), which is a weighted average of EPUs from various countries representing about 80% of world production. See Binge and Boshoff (2020), Glas (2020) and Kozeniauskas et al. (2018) for a discussion of the different methodologies for approximating economic uncertainty.

Finally, with the exception of Abdou et al. (2020), who employed an auto-regressive distributed lag (ARDL) model to study the long-run relationship between economic insecurity and age and gender-specific suicide rates in the US, in all the other studies the relationship between uncertainty and suicide was analysed by means of panel models.

The contribution of this study is twofold. On the one hand, given the abundant evidence of the adverse effect that unemployment has on suicide (Fountoulakis et al., 2014; Huikari and Korhonen, 2021; Nordt et al., 2015), the present study seeks to delve into the financial and labour dimensions of economic uncertainty. With this aim, we use two recent survey-based methods to proxy economic uncertainty using expectations: a geometric indicator of disagreement (Claveria, 2021) and a Knightian measure of uncertainty (Dibiasi and Iselin, 2021). Campaniello et al. (2017) showed the importance of expectations on the risk of suicide. On the other hand, we opt for a non-linear autoregressive distributed lag (NARDL) framework to allow for both symmetric and asymmetric effects of uncertainty on suicide rates. In addition to allowing the modelling of the existing non-linearities in the relationship between both variables, this more general approach also makes it possible to incorporate both stationary and non-stationary variables and compute the dynamic multipliers in order to plot the evolution of the response of suicide rates to unit changes in uncertainty.

In order to assess the long-term relationship between uncertainty and suicide mortality, the analysis focuses on England, where the Office for National Statistics publishes the series from 1981 onwards. We use annual data at national and regional level and split the sample by gender to study the different mechanisms through which economic, financial and labour uncertainty end up influencing male and female suicide rates. Therefore, given the increased uncertainty caused by the COVID-19 pandemic, the study aims to shed some light on the incidence of increased uncertainty on suicide mortality in the UK, breaking down the analysis both at the regional level and by gender.

The study is structured as follows. Section 2 describes the data and the methodology that were used to proxy different dimensions of economic uncertainty. Section 3 presents the model. Section 4 discusses the results. Finally, Section 5 draws some conclusions and offers suggestions for future research.

2. Data

This study uses the suicide mortality rate, measured as the number of suicide deaths in a year per 10000 population published by the Office for National Statistics (https://www.ons.gov.uk/). The paper analyses the temporal evolution of the annual suicide rates in England from 1985 to 2020, for all English regions (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East, London, South East, South West). We also use information on unemployment rates and GDP data from the Office for National Statistics as control variables.

We compute and evaluate different proxies of economic uncertainty. As noted by Dibiasi and Iselin (2021), the question of what exactly is meant by economic uncertainty, and how it can be measured, are still the subject of debate. Following Binge and Boshoff (2020), the different approaches to proxy economic uncertainty can be grouped into five categories: disagreement among professional forecasters (e.g., Lahiri and Sheng, 2010; Rossi and Sekhposyan, 2017); responses from business and consumer surveys (Bachmann et al., 2013; Claveria, 2021); econometrically-constructed measures (Jurado et al., 2015; Meinen and Roehe, 2017); those based on financial data (Basu and Bundick 2012; Bekaert et al. 2013) and text-based proxies (Baker et al., 2016; Ghirelli et al., 2019).

The first two alternatives are based on dispersion metrics that vary depending on the type of survey information they use as input (Mokinski et al., 2015; Rossi and Sekhposyan, 2015). The ex-post nature of the third approach, and the fact that developments of the stock market only partially reflect developments of the real economy (Girardi and Reuter, 2017), has made Baker et al.'s (2016) EPU index the most widely used text-based uncertainty proxy. In this study, we use the EPU index for the UK and also for the US. All EPU data is available for free at http://www.policyuncertainty.com/index.html.

At the same time, a growing number of researchers are beginning to use qualitative information from opinion polls to approximate uncertainty (Altig et al., 2020; Rich and Tracy, 2021). This approach allows proxying uncertainty by means of agents' expectations about a wide range of economic variables. The European Commission conducts monthly consumer tendency surveys in which consumers are asked how they think their financial situation or the level of unemployment will change over the next twelve months. In this study, we propose using the information coming from those two survey questions to compute two additional proxies of uncertainty. On the one hand, following Dibiasi and Iselin (2021), we use the share of consumers unable to formalise expectations in order to compute a Knightian-type uncertainty measure. The authors proposed using the share of respondents that, when surveyed, explicitly answered that they did not know the expected direction of their expectations (*N*). Hence, in this study we use the share of consumers that respond that they do not know the expected direction of their financial situation (*N*_fi) and of unemployment (*N*_un). Thus, these survey indicators capture the proportion of consumers that are not able to formalise expectations about both survey variables, respectively.

On the other, we use the geometric discrepancy indicator (*DIS*) proposed by Claveria (2021) to quantify the proportion of disagreement in consumer expectations. Each of these indicators is computed for each of the two survey questions—the financial situation and unemployment—in order to generate both a 'financial uncertainty' indicator (*DIS*_fi) and a 'labour market uncertainty' (*DIS*_un) indicator.

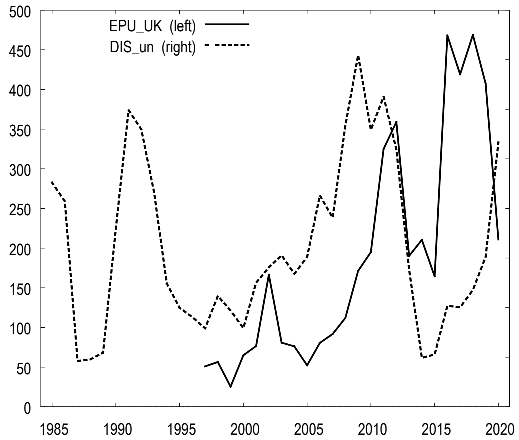
In the survey, consumers are faced with six response options: "a lot better/sharp increase" (*PP*), "a little better/light increase" (*P*), "stay the same" (*E*), "a little worse/slight fall" (*M*), "a lot worse/sharp fall" (*MM*), and a "don't know" category (*N*). The aggregated percentages of the individual replies in each category are respectively denoted as *PP*, *P*, *E*, *M*, *MM* and *N*. Given that opinion polls seek to discriminate between respondents who expect an increase in the variable and those who expect a decrease, in the present study we opted for grouping all positive responses in *P* and all negative ones in *M*, while the "don't know" share is equidistributed between the different options. Given that the sum of all proportions adds up to 100%, we can compute the discrepancy indicators as:

$$DIS_t = 1 - \left[\frac{\sqrt{\left(PP_t + P_t + {}^{N_t}/_3 - {}^{1}/_3\right)^2 + \left(E_t + {}^{N_t}/_3 - {}^{1}/_3\right)^2 + \left(MM_t + M_t + {}^{N_t}/_3 - {}^{1}/_3\right)^2}}{\sqrt{{}^{2}/_3}} \right] \quad (1)$$

This metric is bounded between zero and one, and therefore it is directly interpretable as proportion, where 0 is the point of minimum disagreement among consumers, when one category draws all the answers, and 1 the point of maximum disagreement, in which the answers are equidistributed among the three response categories. Since the survey is conducted on a monthly basis, all survey data are averaged for each year in order to generate annual series of disagreement.

Figure 1 compares the evolution of the EPU index and the labour market uncertainty indicator. The graph shows that both metrics covary during the sample period. Claveria and Sorić (2023a) showed that there was a high correlation between Knightian uncertainty (*N*) and disagreement (*DIS*) for the UK, which increased during the periods of extreme uncertainty such as the 2008 crisis or the current one.

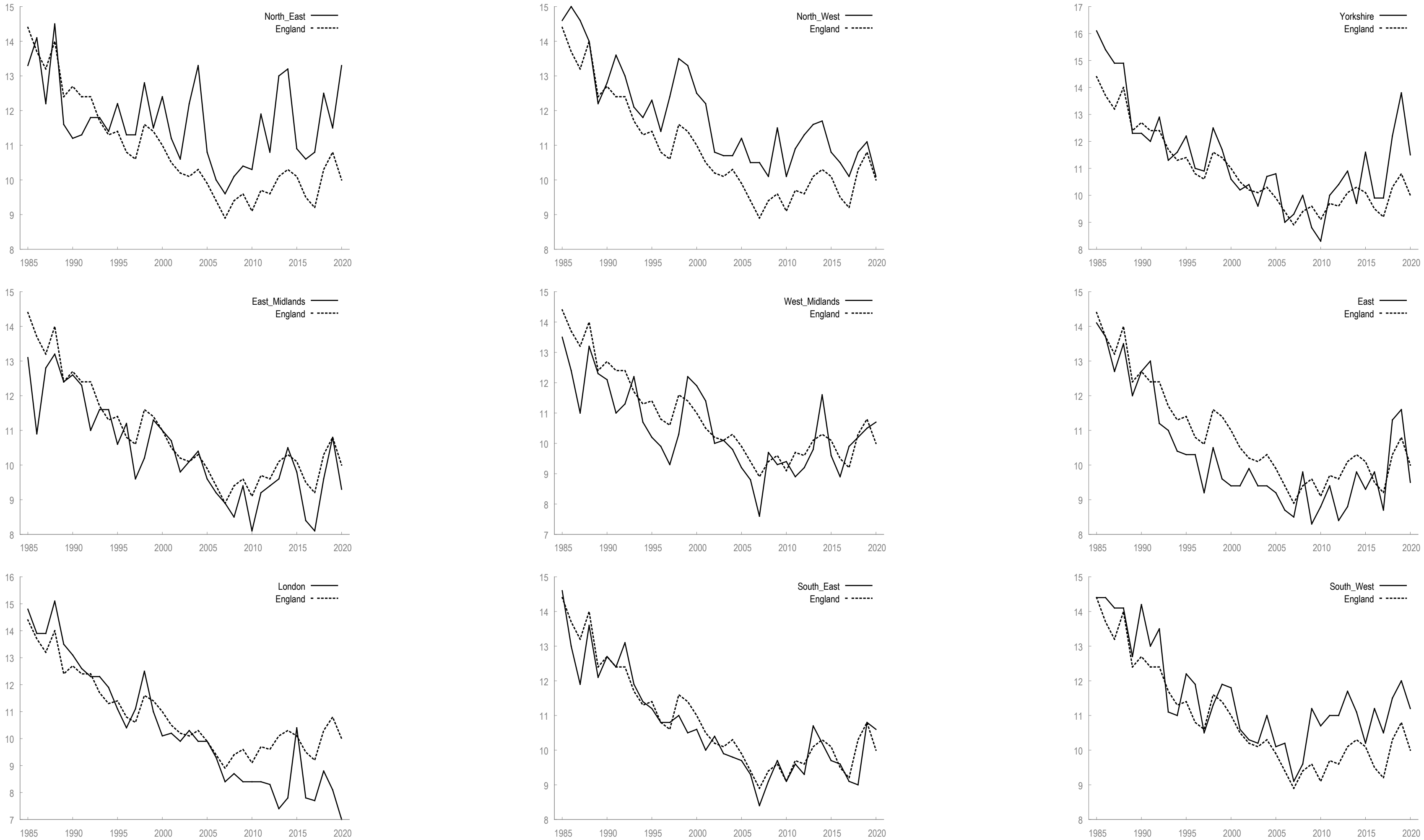
Figure 1. EPU and labour market uncertainty in the UK



Note. The black line represents the disagreement regarding consumers' unemployment expectations (*DIS*_un), while the black-dotted line the evolution of the economic policy uncertainty (EPU) index.

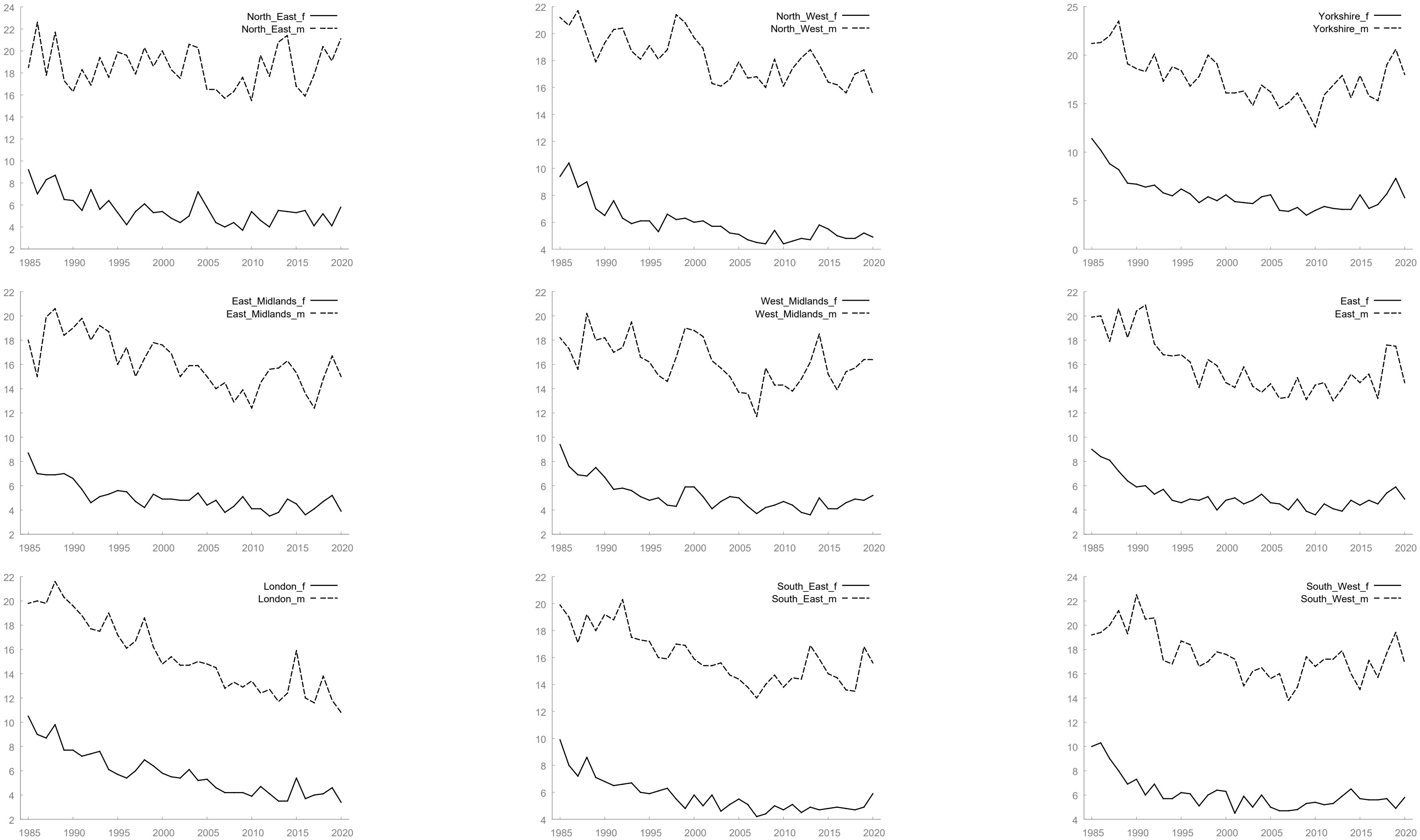
Figure 2 shows the evolution of suicide rates by region compared to that in England and Figure 3 the evolution by gender at a regional level. The graphs displays a decreasing trend at the aggregate level. However, since 2006 there seems to be an upturn in the trend (Coope et al., 2014; Iacobucci, 2020; Qiao et al., 2022). This slight but steady increase is most evident in the North East, Yorkshire, West Midlands, and the South West, as opposed to other regions like London.

Figure 2. Evolution of suicide rates (1985-2020)



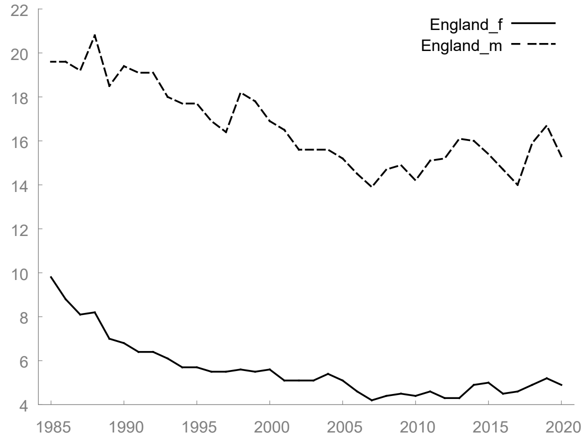
Note. The black line represents the evolution of suicide rates in each region, while the black-dotted line the evolution in England.

Figure 3. Evolution of suicide rates by gender at a regional level (1985-2020)



Note. The black line represents the evolution of suicide rates for females (_f), while the black-dotted line the evolution for males (_m).

Figure 4. Evolution of suicide rates by gender in England (1985-2020)



Note. The black line represents the evolution of suicide rates for females (_f), while the black-dotted line the evolution for males (_m).

The graphs in Figure 3 display how suicide mortality rates between women and men show a practically identical evolution, however at an aggregate level (Figure 4), it is palpable that suicide rates among men triple those among women.

This is further evidenced in Table 1, which contains the average and the coefficient of variation of annual suicide rates and the rest of variables over the period 1985–2020. The variation coefficient is a standardised measure of relative dispersion, expressed as the percentage of the standard deviation to the mean. Results in Table 1 indicate that both the level and the dispersion of the EPU proxy for economic uncertainty is higher for the UK than for the US. Regarding the survey-based proxies of uncertainty the same can be said for labour market uncertainty with respect to financial uncertainty. Regarding the average suicide rates, the differences across regions are minimal, although the differences by gender are remarkable, as shown in Figure 3 and 4. The male suicide rate is triple that of women in all regions. Notwithstanding, the relative dispersion of females' suicide rate doubles that of males.

Finally, we run the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Results are presented in Table 2. In the KPSS test (Kwiatkowski et al., 1992) the null hypothesis that the time series is stationary around a deterministic trend is tested against the alternative of a unit root. Cases in which the null hypothesis of stationarity cannot be rejected at the 5% significance level are marked in bold. While in most cases the null hypothesis is rejected, we obtain mixed evidence.

Table 1. Summary statistics (1985-2020)

Variables / Economic uncertainty proxies	Mean	Variation Coefficient		
EPU_US	119.7	38.6%		
EPU_UK	188.5	75.7%		
DIS_fi	0.2	27.4%		
DIS_un	4.8	40.5%		
N_fi	0.3	53.4%		
N_un	5.0	44.9%		
Control variables				
GDP	1676.9	20.9%		
Unemployment	6.9	30.9%		
Suicide rates	Females		Males	
	Mean	Variation Coefficient	Mean	Variation Coefficient
England	5.6	23.8%	16.7	11.2%
North East (NE)	5.6	23.8%	18.6	10.1%
North West (NW)	6.0	24.3%	18.2	9.7%
Yorkshire and the Humber (YH)	5.7	31.0%	17.6	13.5%
East Midlands (EM)	5.1	22.5%	16.2	13.2%
West Midlands (WM)	5.2	24.0%	16.2	11.8%
East (EE)	5.2	24.1%	15.9	14.7%
London (LDN)	5.8	32.1%	15.6	19.3%
South East (SE)	5.7	22.1%	16.1	12.2%
South West (SW)	6.1	22.3%	17.5	11.0%

Table 2. Test for stationarity – KPSS test statistics

Variables	All	By gender	
Economic uncertainty proxies		Females	Males
EPU_US	0.524	–	–
EPU_UK	0.510	–	–
DIS_fi	0.753	–	–
DIS_un	0.751	–	–
N_fi	**0.424**	–	–
N_un	0.862	–	–
Control variables			
GDP	0.966	–	–
Unemployment	0.765	–	–
Suicide rates			
England	0.510	0.569	0.938
North East (NE)	0.753	0.602	0.730
North West (NW)	0.751	**0.277**	2.529
Yorkshire and the Humber (YH)	**0.424**	0.788	2.527
East Midlands (EM)	0.862	0.595	0.592
West Midlands (WM)	0.966	**0.146**	0.708
East (EE)	0.753	**0.280**	2.987
London (LDN)	0.751	0.926	1.100
South East (SE)	**0.424**	0.842	0.847
South West (SW)	0.862	0.793	1.134

Notes. Estimation period 1985–2020. Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test for stationarity (Kwiatkowski, Phillips, Schmidt and Shin, 1992). Critical values i) with trend: 0.122 (10%), 0.149 (5%), 0.211 (1%); ii) with no trend: 0.353 (10%), 0.462 (5%), 0.717 (1%). Null hypothesis: time series is stationary around a deterministic trend (i.e. the process is trend-stationary), against the alternative of a unit root. Cases in which the null hypothesis of stationarity cannot be rejected at the 5% significance level are marked in bold.

3. Methodology

In this section, following a similar approach to Claveria and Sorić (2023b), we combine two different modelling strategies in order to obtain a granular perspective on the relationship between uncertainty and suicide. First, we use Shin et al.'s (2014) NARDL model. This approach allows us to capture the interactions both in the short run and in the long run, as well as to test for the existence of a cointegration relationship between the different proxies of uncertainty and male and female suicide rates, henceforth denoted as SR. This more general setting also allows to analyse the existence of asymmetries between both variables. To do so, we decompose changes in uncertainty into positive and negative as follows:

$$\Delta SR_t = a_0 + \rho SR_{t-1} + \theta^+ X_{t-1}^+ + \theta^- X_{t-1}^- + \delta UN_{t-1} + \varphi GDP_{t-1} + \sum_{j=1}^{p-1} a_j \Delta SR_{t-j} + \sum_{j=0}^{q^+-1} \pi_{1,j}^+ \Delta X_{t-j}^+ + \sum_{j=0}^{q^--1} \pi_{1,j}^- \Delta X_{t-j}^- + e_t, \quad (2)$$

Where X refers to each of the six assessed economic uncertainty proxies. Positive and negative changes are respectively denoted as $X_t^+ = \sum_{j=1}^{t} max(\Delta x_j, 0)$ and $X_t^- = \sum_{j=1}^{t} min(\Delta x_j, 0)$. Finally, unemployment (UN) and GDP, which have been found to be related to suicide rates (Chen et al., 2012; Iglesias-García et al., 2017; Kim, 2022; Madianos et al., 2014), are used as control variables in the model.

The choice of this more general type of model, which until now has been rarely used in this field up until now (Botha and Nguyen, 2022; Chang and Chen, 2017), is justified for three reasons. First, our dataset comprises both stationary and nonstationary variables, a case that often adds noise to the model. The NARDL framework neatly accommodates for such situations and provides credible estimates regardless of the integration order of assessed variables (Shin et al., 2014). Second, we have a limited sample size at hand—annual data from 1985 to 2020—, so the NARDL general-to specific procedure (Greenwood-Nimmo and Shin, 2013) allows us to exclude the insignificant lags of each system variable and preserve valuable degrees of freedom. Third, we aim to examine whether the suicide rate reacts asymmetrically to positive and negative changes in economic uncertainty, as in a recent paper Abdou et al. (2022) found evidence that the relationship between economic uncertainty and suicide in the US was context-dependent and asymmetric, i.e. the effects of unexpected increases in uncertainty were different from unexpected decreases.

The optimal lag structure of the NARDL model (p, q^{+} and q^{-}) is established in a step-wise fashion. Namely, equation (1) is estimated in the most general form, starting from p=q^{+}=q^{-}= 4, and then all insignificant regressors are iteratively dropped out, following a 5% significance stopping criterion. This empirical approach was introduced by Greenwood-Nimmo and Shin (2013) and to improve the signal to noise ratio and avoid misspecifications that might lead to spurious results.

Additionally, we run a conventional Wald test to assess the null hypothesis of no cointegration ($\boldsymbol{H_0}$: $\rho = \theta^{+} = \theta^{-} = 0$). It is important to note that we do not impose any type of asymmetric reactions in the model. On the contrary, we empirically test for long-run symmetry ($\boldsymbol{H_0}$: $\theta^{+} = \theta^{-}$) and short-run symmetry ($\sum_{j=0}^{q^{+}-1} \pi_{1,j}^{+} = \sum_{j=0}^{q^{-}-1} \pi_{1,j}^{-}$), again via a Wald test. The model in Equation (2) is then re-estimated conditional on the results of these tests. The purpose of this modelling strategy is to capture the true data generating process and obtain reliable and unbiased estimates. Equations (3) to (5) show the potential final NARDL specifications, depending on the results of short-run and long-run symmetry tests.

If the null hypothesis of long-run symmetry is not rejected, equation (2) becomes:

$$\Delta SR_t = a_0 + \rho SR_{t-1} + \theta X_{t-1} + \delta UN_{t-1} + \varphi GDP_{t-1} + \sum_{j=1}^{p-1} a_j \Delta SR_{t-j} + \sum_{j=0}^{q^{+}-1} \pi_j^{+} \Delta X_{t-j}^{+} + \sum_{j=0}^{q^{-}-1} \pi_j^{-} \Delta X_{t-j}^{-} + e_t \tag{3}$$

If the null of short-run symmetry is not rejected, the model is specified as:

$$\Delta SR_t = a_0 + \rho SR_{t-1} + \delta UN_{t-1} + \varphi GDP_{t-1} + \theta^{+} X_{t-1}{}^{+} + \theta^{-} X_{t-1}{}^{-} + \sum_{j=1}^{p-1} a_j \Delta SR_{t-j} + \sum_{j=0}^{q-1} \pi_j \ \Delta X_{t-j} + e_t \tag{4}$$

Finally, if both types of symmetries are present in the equation at the 5% significance level, the model comes down to a pure ARDL process:

$$\Delta SR_t = a_0 + \rho SR_{t-1} + \delta UN_{t-1} + \varphi GDP_{t-1} + \theta X_{t-1} + \sum_{j=1}^{p-1} a_j \Delta SR_{t-j} + \sum_{j=0}^{q-1} \pi_j \ \Delta X_{t-j} + e_t \tag{5}$$

This exact estimation procedure is carried out for the England as a whole, and then for each region and for males and females independently.

We additionally perform two diagnostic tests to check if the error terms of these specifications can be described as white noise process. To be specific, we run a Ljung-Box test for autocorrelation of 4th order, and Engle's autoregressive conditional heteroscedasticity (ARCH) test of 4th order. If one of these two tests, or both, reject the null hypothesis at the 5% significance level, we employ the Newey-West autocorrelation- and heteroscedasticity-consistent (HAC) estimator.

Finally, in case of significant asymmetries (short-run, long-run, or both), we compute and graphically present the dynamic multipliers (m_h^+), i.e. the responses of suicide rates to positive and negative unit changes in uncertainty This concept can be understood as an asymmetric version of impulse response functions in vector autoregressive models. The multipliers are computed for each forecast horizon h:

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial SR_{t+j}}{\partial X_t^+} \text{ and } m_h^- \sum_{j=0}^{h} \frac{\partial SR_{t+j}}{\partial X_t^-}, \text{ where } h = 0, 1, 2, \dots, 12 \tag{6}$$

Additionally, in order to examine if the relationship between the different dimensions of economic uncertainty and suicide rates is time-dependent, we use a state-space representation of a regression model with time-varying parameters (see e.g. Durbin and Koopman, 2012). The state-space model can be depicted through two equations, the observation equation (7) and the state equation (8):

$$SR_t = z_t' \beta_t + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{N}(0, \sigma_{t.\varepsilon}^2) \tag{7}$$

$$\beta_{t+1} = \beta_t + \eta_t, \quad \eta_t \sim \mathrm{N}(0, \mathrm{Q}), t = 1, \dots, T \tag{8}$$

where T is sample size, SR_t denotes the suicide rate, $\beta_t' = \begin{pmatrix}\beta_{t,0} & \beta_{t,1} & \dots & \beta_{t,m}\end{pmatrix}$ is an unobserved $(m+1) \times 1$ state vector, $Q = diag(\sigma_{t,1}{}^2, \sigma_{t,2}{}^2, \dots, \sigma_{t,m}{}^2)$ is a diagonal $m \times m$ covariance matrix, vector $z_t' = \begin{pmatrix}1 & x_{t,1} & x_{t,2} \dots & x_{t,m}\end{pmatrix}$ is the $(m+1) \times 1$ regressor vector, $\eta_t' = (\omega_{t,1}, \omega_{t,2} \dots \omega_{t,m})$ is the error term vector, and m is the number of state variables. Parameter $\beta_{t,0}$ is usually referred to as local level. In our analysis, the regressor vector is defined as $z_t' = (1 \;\; X_t \;\; UN_t \;\; GDP_t)$.

We use estimators that are conventional for this type of model. To estimate the unknown variances in the covariance matrix $\boldsymbol{Q}$ we use the Broyden–Fletcher–Goldfarb–Shanno algorithm (Durbin and Koopman, 2012), while $\boldsymbol{\beta_t}$ are obtained using the diffuse Kalman filter (de Jong, 1991). A crucial issue is that $\boldsymbol{\beta_t}$ are modelled as a random walk process. However, this does not imply that the model parameters have to be time-varying.

On the contrary, the local level and the uncertainty parameter can be either fixed or time-varying depending on the corresponding variances in $\boldsymbol{Q}$ being deterministic or stochastic. The parameters of our control variables, UN and GDP, are treated as fixed. Namely, the idea is to control for the macroeconomic outlook and assess the relationship between different dimensions of uncertainty and suicide mortality. Given that each of our two focal parameters, i.e. the local level and the uncertainty parameter, can be either fixed or time-varying, this yields 2^2=4 different specifications of the model contained in equations (7) and (8). We choose the optimal model for each uncertainty proxy via the Akaike information criterion.

4. Results

In this section, we evaluate the relationship between different proxies of uncertainty and suicide in England, controlling for unemployment and economic growth, and breaking down the analysis at a regional level and by gender. While empirical evidence shows that uncertainty shocks are an important exogenous source of economic fluctuation (Bloom, 2009, 2014; Caldara et al., 2016; Istiak and Serletis, 2018; Sorić and Lolić, 2017), only a few recent studies have examined the link between economic uncertainty and suicide (Abdou et al., 2020, 2022; Antonakakis and Gupta, 2017; Claveria, 2022; de Bruin et al., 2020; Vandoros et al., 2019; Vandoros and Kawachi, 2021).

Table 3 summarises the results obtained in the NARDL analysis, for the country as a whole and separately for males and females, while Tables 4 to 6 show the results across regions. At conventional significance levels, most of the six different assessed uncertainty proxies exhibit a significant long-run relationship with suicide rates. The exceptions to this rule are found for males (Table 3) and for the East region (Table 6). In a similar vein, we also assess Granger causality between economic, financial and labour uncertainty with and suicide mortality by jointly testing the significance of all lagged values of uncertainty. The concept of Granger causality is based on the notion of predictive accuracy. A variable is said to Granger-cause another variable if past values of the former contain information that helps to predict the latter beyond the information contained in its past values alone (Granger, 1969). The results presented in Tables 3 to 6 provide firm evidence that economic uncertainty can be used for short-run predictions of future suicide rates for the country as a whole, as well as at a regional level, with the exception of the South West.

However, results widely vary depending on the uncertainty proxy, being the EPU index for the UK the one showing the best performance.

Table 3. NARDL cointegration analysis – Effect of uncertainty on suicide rates by gender

Uncertainty measure	Type of asymmetry	Cointegration test – F value	Granger-causality test – F value	θ^+	θ^-
England					
EPU_UK	SR	11.46**	9.89**	0.005**	
EPU_US	SR & LR	10.04**	5.09**	0.008	-0.021*
DIS_fi	-	6.81*	5.35**	-0.734	
N_fi	-	3.76	-	0.077	
DIS_un	SR	6.04*	4.95*	-2.092*	
N_un	-	6.08*	-	0.098	
Females					
EPU_UK	-	13.62**	2.27	0.002*	
EPU_US	SR & LR	9.87**	4.99**	0.004	-0.009*
DIS_fi	LR	7.89**	9.48**	2.296	-3.386*
N_fi	-	2.34	8.62**	0.042	
DIS_un	SR & LR	9.29**	4.71*	0.632	-1.534**
N_un	SR	9.51**	0.92	0.034	
Males					
EPU_UK	SR	14.90**	11.60**	0.008**	
EPU_US	SR & LR	12.34**	11.89**	0.005	-0.387**
DIS_fi	-	4.67	0.04	-5.488	
N_fi	-	3.84	-	0.089	
DIS_un	-	4.28	0.02	-0.683	
N_un	-	3.22	3.36	0.087	

Notes. ** Significance at the 0.01 level, * at the 0.05 level. Missing data in the “Type of asymmetry” column indicates a purely symmetric ARDL model. Missing data in the “Granger causality test F value” indicates that the optimal model specification includes no lags of economic uncertainty, so the Granger causality test could not be performed.

Table 4. NARDL cointegration analysis – Effect of uncertainty on suicide rates by region

Uncertainty measure	Type of asymmetry	Cointegration test – F value	Granger-causality test – F value	θ^{+}	θ^{-}
North East					
EPU_UK	-	9.41**	7.51**	0.018**	
EPU_US	SR	21.48**	8.16**	0.029*	
DIS_fi	SR & LR	17.40**	6.25**	19.087	-20.185**
N_fi	-	8.91**	-	0.118	
DIS_un	LR	6.37*	0.91	-1.242	-2.230
N_un	-	10.36**	-	0.180	
North West					
EPU_UK	-	3.40	1.05	0.006	
EPU_US	-	5.53*	-	0.002	
DIS_fi	SR & LR	7.70**	7.03*	5.278	-2.032
N_fi	-	6.92**	-	0.125	
DIS_un	-	5.52*	-	-0.323	
N_un	-	7.80**	-	0.136	
Yorkshire and the Humber					
EPU_UK	-	13.74**	4.34*	0.010**	
EPU_US	SR	14.64**	7.34**	0.030*	
DIS_fi	-	7.23**	0.10	-6.329	
N_fi	LR	3.51	-	-0.033	0.272
DIS_un	SR	9.74**	5.60*	-6.761**	
N_un	- ^{HAC}	24.11**	-	0.228**	

Notes. ** Significance at the 0.01 level, * at the 0.05 level. Missing data in the “Type of asymmetry” column indicates a purely symmetric ARDL model. Missing data in the “Granger causality test F value” indicates that the optimal model specification includes no lags of economic uncertainty, so the Granger causality test could not be performed.

Table 5. NARDL cointegration analysis – Effect of uncertainty on suicide rates by region

Uncertainty measure	Type of asymmetry	Cointegration test – F value	Granger-causality test – F value	θ^{+}	θ^{-}
East Midlands					
EPU_UK	SR	16.89**	4.63*	0.007**	
EPU_US	SR	4.97*	7.26**	-0.025**	
DIS_fi	-	13.41**	-	-7.385**	
N_fi	SR	6.69*	2.46	-0.184	
DIS_un	-	9.04**	-	-1.601	
N_un	SR	9.97**	7.53*	0.228*	
West Midlands					
EPU_UK	SR	11.01**	7.27*	0.005**	
EPU_US	-	6.84*	-	0.011	
DIS_fi	-	6.96**	-	-5.696	
N_fi	-	5.66*	-	0.126	
DIS_un	-	5.99*	-	-1.345	
N_un	SR	10.38**	5.17*	0.319**	
East					
EPU_UK	SR	3.79	12.99**	0.003	
EPU_US	-	1.20	-	0.007	
DIS_fi	-	0.51	-	-2.088	
N_fi	LR	1.48	-	0.529	-0.186
DIS_un	-	1.08	-	-1.203	
N_un	LR	0.44	-	0.089	0.087

Notes. ** Significance at the 0.01 level, * at the 0.05 level. Missing data in the "Type of asymmetry" column indicates a purely symmetric ARDL model. Missing data in the "Granger causality test F value" indicates that the optimal model specification includes no lags of economic uncertainty, so the Granger causality test could not be performed.

Table 6. NARDL cointegration analysis – Effect of uncertainty on suicide rates by region

Uncertainty measure	Type of asymmetry	Cointegration test – F value	Granger-causality test – F value	θ^{+}	θ^{-}
London					
EPU_UK	SR	23.57**	20.66**	0.005**	
EPU_US	LR	-	5.89*	0.002	-0.018
DIS_fi	-	15.29**	6.80**	-6.009*	
N_fi	LR	8.73**	19.42**	-0.255*	0.011
DIS_un	-	11.66**	-	-2.109*	
N_un	-	8.93**	-	0.122	
South East					
EPU_UK	SR	20.77**	10.28**	0.009**	
EPU_US	SR	8.80**	2.32	0.032**	
DIS_fi	SR & LR	3.62	10.07**	-5.616*	-18.990**
N_fi	LR	5.62	-	-0.198	0.154
DIS_un	SR & LR	4.90	5.29*	-0.188	-1.130
N_un	-	5.02*	-	0.072	
South West					
EPU_UK	-	5.80*	-	0.004	
EPU_US	-	4.96*	-	0.009	
DIS_fi	-	13.65**	-	-10.601**	
N_fi	-	3.77	-	-0.043	
DIS_un	SR	5.29*	3.53	-0.876	
N_un	-	4.10	-	0.074	

Notes. ** Significance at the 0.01 level, * at the 0.05 level. Missing data in the “Type of asymmetry” column indicates a purely symmetric ARDL model. Missing data in the “Granger causality test F value” indicates that the optimal model specification includes no lags of economic uncertainty, so the Granger causality test could not be performed.

What strikes the most at first glance is the noticeable difference in the responses to uncertainty shocks by gender. Females seem to be much more responsive to economic uncertainty, especially to decreases of uncertainty. This result is partly in line with recent research by Abdou et al. (2022), who found significant asymmetries in the adverse effect of uncertainty on suicide mortality between women and men in the US. However, the authors encountered that extreme unexpected increases induced suicide in males while decreases were not statistically significant. These partial differences in the obtained results may stir in part from the sample size, the socio-cultural differences between the two countries. To this it should be added the lower suicide rates in the UK and the greater relative dispersion observed among female suicide rates (Table 1).

The asymmetries found by gender are in keeping with recent findings related to the marked differences by sex with regards to the impact of several economic factors on suicide behaviour. In this regard, Bommersbach et al. (2022) recently found that in the US women had 1.78 greater odds of self-reported lifetime suicide attempts than men. The authors concluded that several risk factors for suicide attempts appear to have significantly different magnitude of association among women and men. Similarly, Yoshioka et al. (2022) found that in Japan the COVID-19 pandemic had a more pronounced impact on suicide rates in women. Sánchez (2021) also obtained evidence of an increase in female suicide rates during the pandemic in Japan. When analysing the effect of austerity policies on mortality rates in the UK between men and women, Walsh et al. (2022) observed changes in trends for both men and women, but found that in the most deprived areas mortality increased between 2010/2012 and 2017/2019 among women but not men.

This finding reveals the difficulty of unraveling the observed differences by gender in the asymmetric impact of uncertainty on suicide rates from other economic factors such as income and inequality. Low income has been proved to be a significant factor contributing to suicide (Choi et al., 2019; Korhonen et al., 2017). In a study for South Korea, Lee et al. (2017) found that men showed high hazard ratios for suicide in almost all socioeconomic position groups, whereas for women high hazard ratios were associated only with low socioeconomic position groups. Lin et al. (2020) for their part, found that night-shift work, sickness absence, work and family stress were positively associated with suicide ideation among working women, and that women with both high work stress and high family stress showed more than five-time odds of suicide ideation.

In the specific case of England, it is worth noting that people living in the most deprived areas have a higher risk of suicide than those living in the least deprived areas (Walsh et al., 2022). Similarly, Baker (2022) found that suicide rates in the most deprived areas between 2017 and 2019 were almost double the rates observed in the least deprived areas. The results obtained in the study suggest that in England, the psychological determinants more characteristic of females—interpersonal and work- and family-related stress—might be more pronounced than other drivers that especially affect men, such as low income.

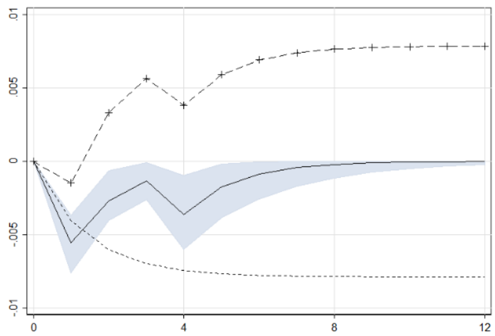
In this sense, we found differences across English regions, obtaining significant asymmetries in six of the nine regions, being the North West, the East and the South West those in which the long-term relationship between uncertainty and the suicide rate was not found statistically significant. By contrast, on the first three regions with higher per capita income—London, South East and the East—this relationship tended to be significant for many of the proxies included in the analysis.

The link between the different dimensions of uncertainty and suicide mortality was found to be significant for many of the proxies used in the analysis, especially for the EPU index both in the UK and the US, and to a lesser extent the disagreement indicator regarding financial expectations (*DIS*_fi). Labour market uncertainty was found to have a significant effect in Yorkshire and the Humber, in the East and the West Midlands and in London, which are together with the North East, the regions with highest unemployment rates, revealing the North-South divide in England. This result highlights the importance of disentangling between the different dimensions of uncertainty.

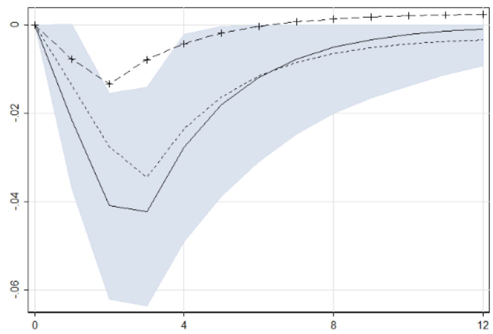
Next, we graph the dynamic multipliers for specifications with statistically significant asymmetries. We regard asymmetry as significant if either the short-run or the long-run asymmetry are significant at the 5% level and the 95% confidence interval of dynamic multiplier asymmetry, i.e. the difference between m_h^+ and m_h^- , does not comprise the value zero. Figure 5 presents the dynamic multipliers of model specifications with significant asymmetries for England as a whole, and Figure 6 for females and males, respectively.

Figure 5. Dynamic multipliers as a response to a unit shock in uncertainty (England)

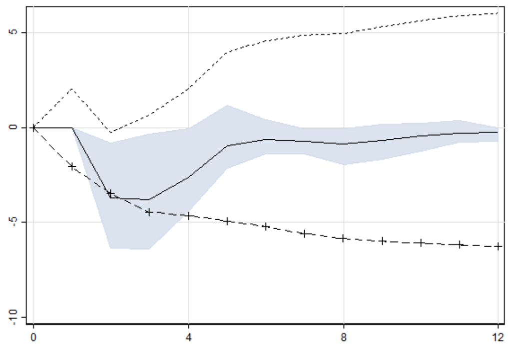
a) EPU_UK



b) EPU_US



c) DIS_un



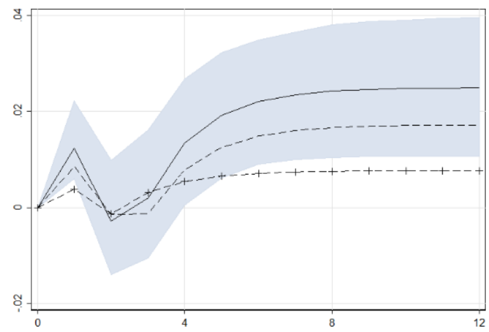
Notes: The horizontal axis depicts years; the vertical axis depicts the suicide mortality rate. Dashed lines are the dynamic multipliers for negative changes of uncertainty. Lines marked with plus signs are the dynamic multipliers for positive changes of uncertainty. Full lines are the differences between the two (asymmetry). Shaded areas are the bootstrapped 95% confidence intervals for asymmetry.

With a few exceptions, the graphs reveal that the suicide rates react more intensively to decreases in the different dimensions of uncertainty than to increases. At the regional level, the two uncertainty proxies for which we obtained robust evidence of asymmetry in most cases are EPU_UK and EPU_US. We therefore depict the dynamic multipliers for these two variables in specifications with significant asymmetries within the regional analysis of suicide rates (Figures 7 and 8, respectively). Again, almost as a rule, we find that the suicide rates are more responsive to negative than to positive changes in economic uncertainty.

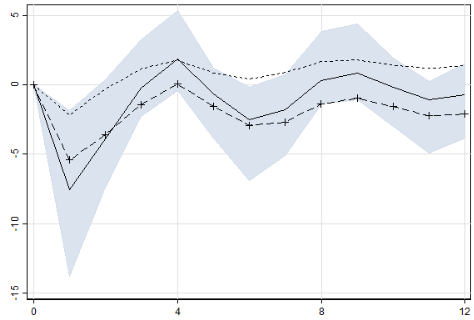
Figure 6. Dynamic multipliers by gender

Females

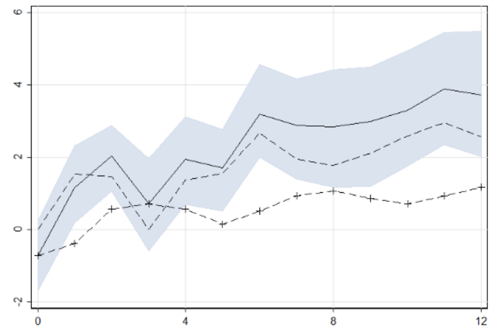
a) EPU_US



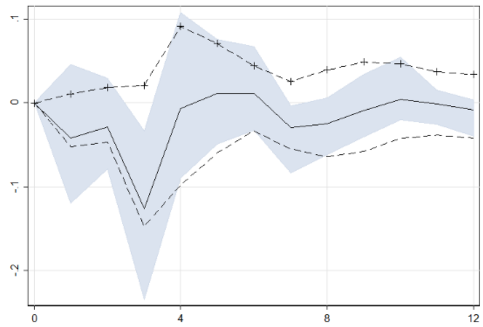
b) DIS_fi



c) DIS_un

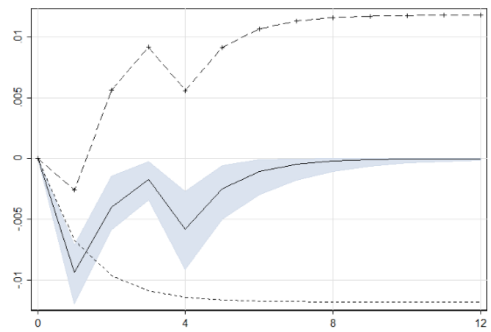


d) N_un

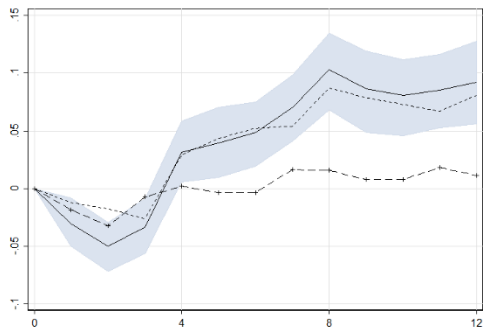


Males

a) EPU_UK



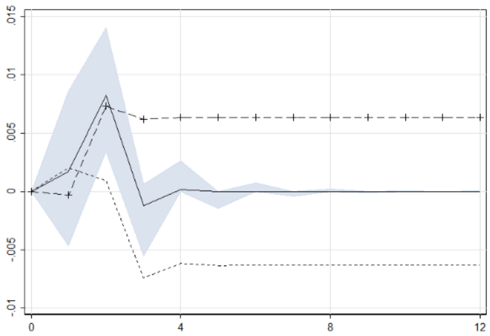
b) EPU_US



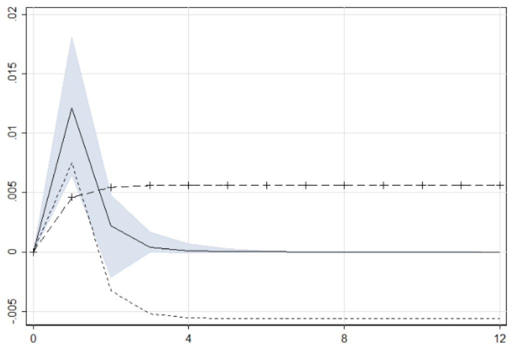
Notes. See Notes of Figure 5.

Figure 7. Dynamic multipliers by region – Response to a unit shock in EPU_UK

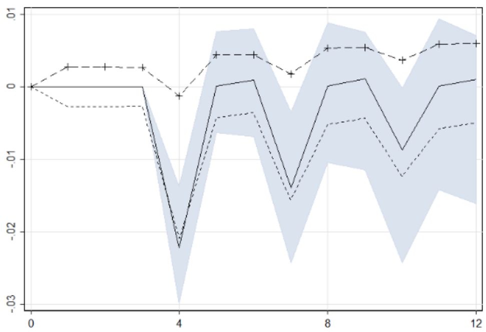
a) East Midlands



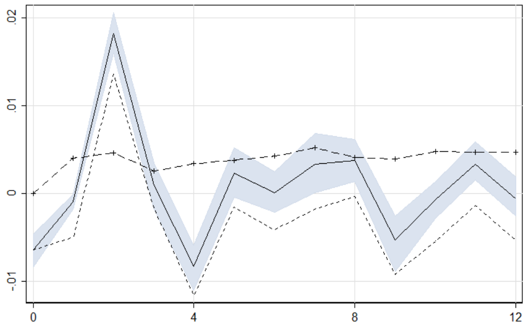
b) West Midlands



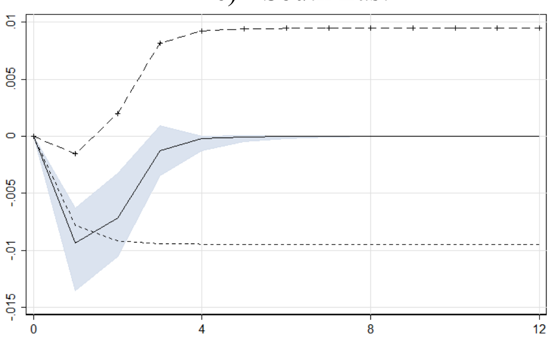
c) East



d) London



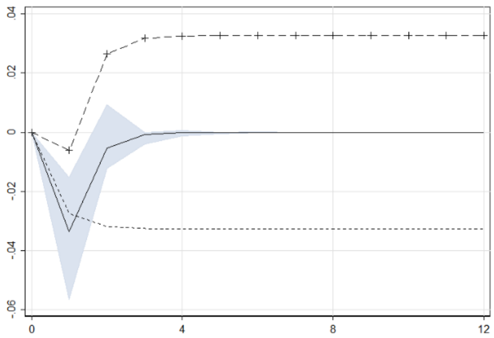
e) South East



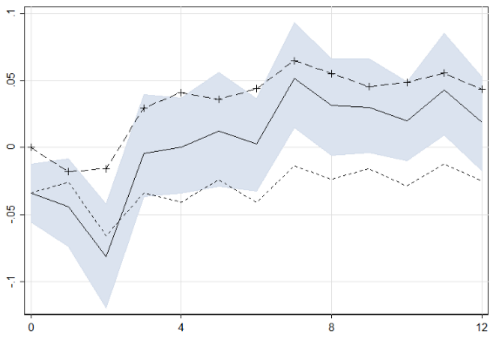
Notes: See notes of Figure 5.

Figure 8. Dynamic multipliers by region – Response to a unit shock in EPU_US

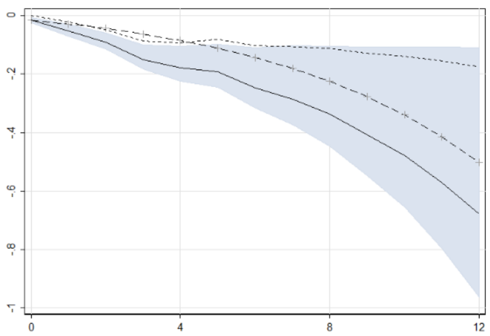
a) North East



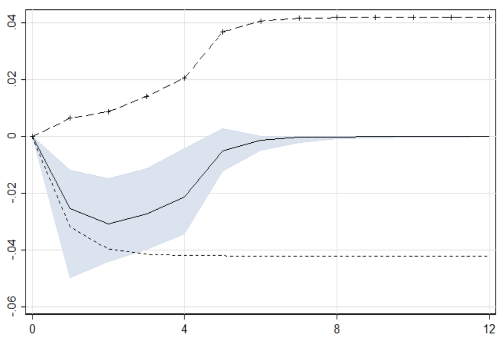
b) Yorkshire and the Humber



c) East Midlands



d) South East



Notes: See notes of Figure 5.

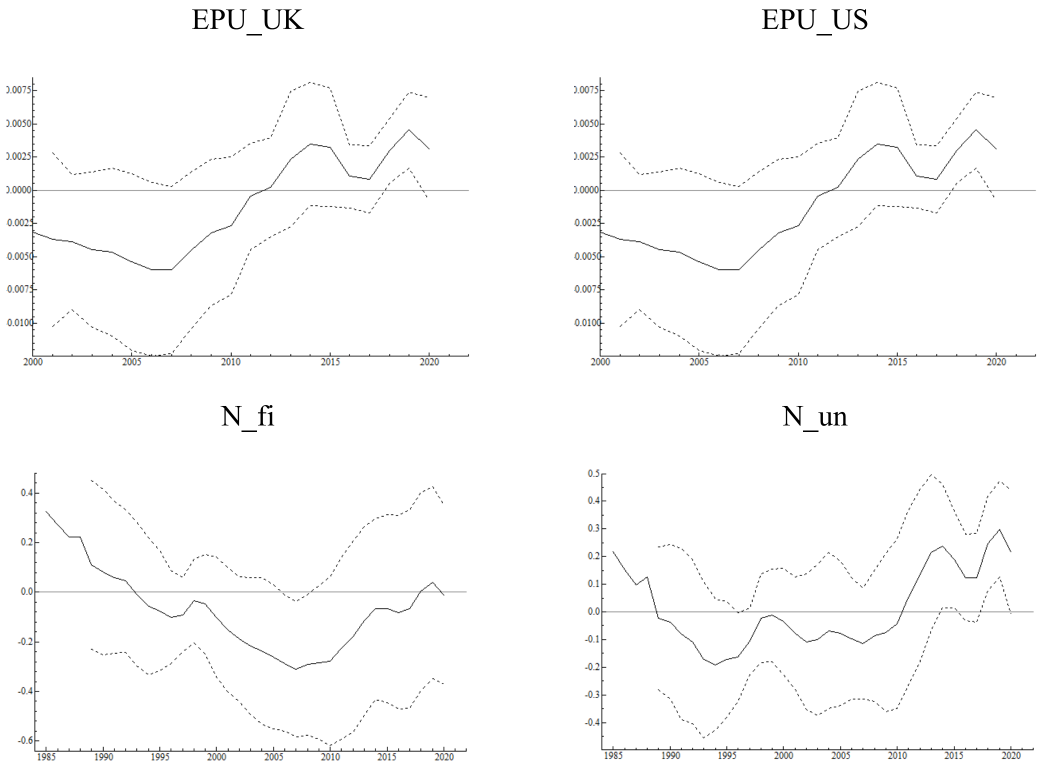
As a robustness check, we have done a similar analysis using a state-space model (equations 7 and 8). Table 7 contains the results of the optimal model specifications, as chosen by the Akaike information criterion, both for females and males and for each uncertainty proxy. In accordance with the NARDL analysis, we test the standardised prediction errors using customary diagnostic tests. In all specifications, the error terms satisfy the assumption of homoskedasticity and are free of autocorrelation at the 5% significance level, so the details are not presented here for brevity. Figures 9 to 11 depict the evolution of the significant time-varying uncertainty parameters, both for the country as a whole (Figure 9), as well as for females and males (Figures 10 and 11). Overall, the obtained time-varying estimations suggest that the pandemic has strengthened the uncertainty-suicide relationship.

Table 7. State-space model – Effect of uncertainty on suicide rates (by gender)

Dependent variable	Uncertainty proxy	Parameters	
		Local level	X_t
England	EPU_UK	17.759**	time-varying
	EPU_US	13.488**	time-varying
	DIS_fi	14.517**	time-varying
	N_fi	16.619**	time-varying
	DIS_un	11.341*	-0.056
	N_un	18.971**	time-varying
England_f	EPU_UK	9.998**	time-varying
	EPU_US	9.413**	time-varying
	DIS_fi	10.655**	-2.694*
	N_fi	7.530*	-0.044
	DIS_un	time-varying	-0.172
	N_un	15.688**	time-varying
England_m	EPU_UK	27.407**	time-varying
	EPU_US	19.963**	time-varying
	DIS_fi	25.424**	-6.993*
	N_fi	24.703**	time-varying
	DIS_un	20.061**	-0.298
	N_un	26.887**	time-varying

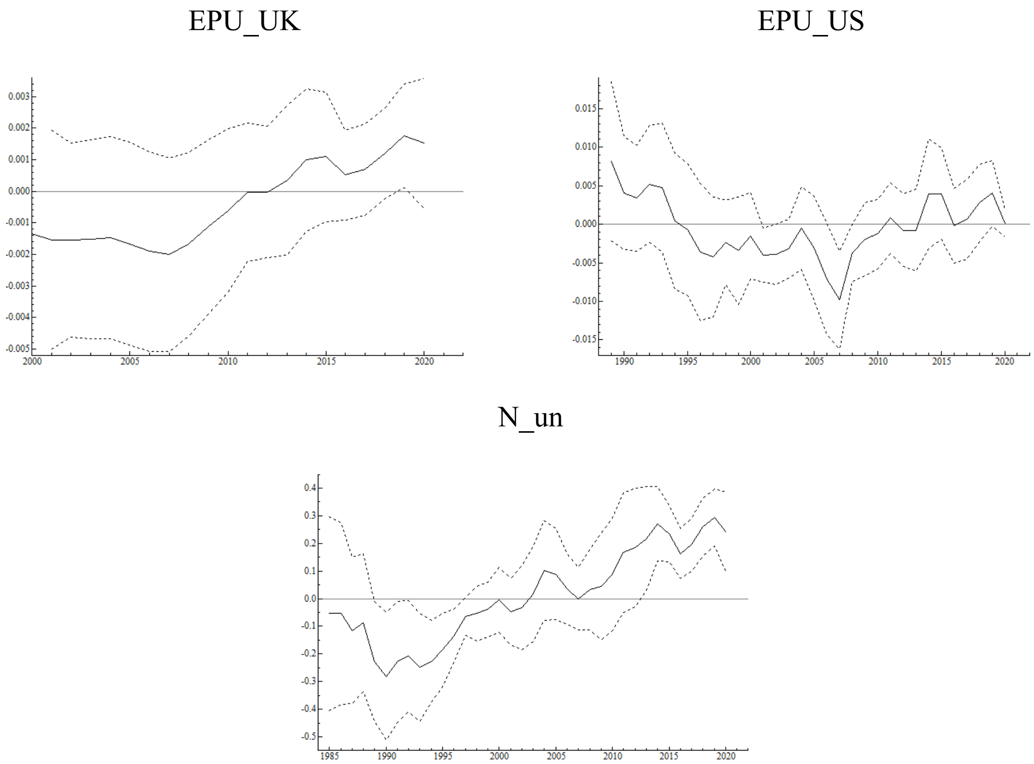
Notes. ** Significance at the 0.01 level, * at the 0.05 level.

Figure 9. Time-varying parameters of economic uncertainty (England)



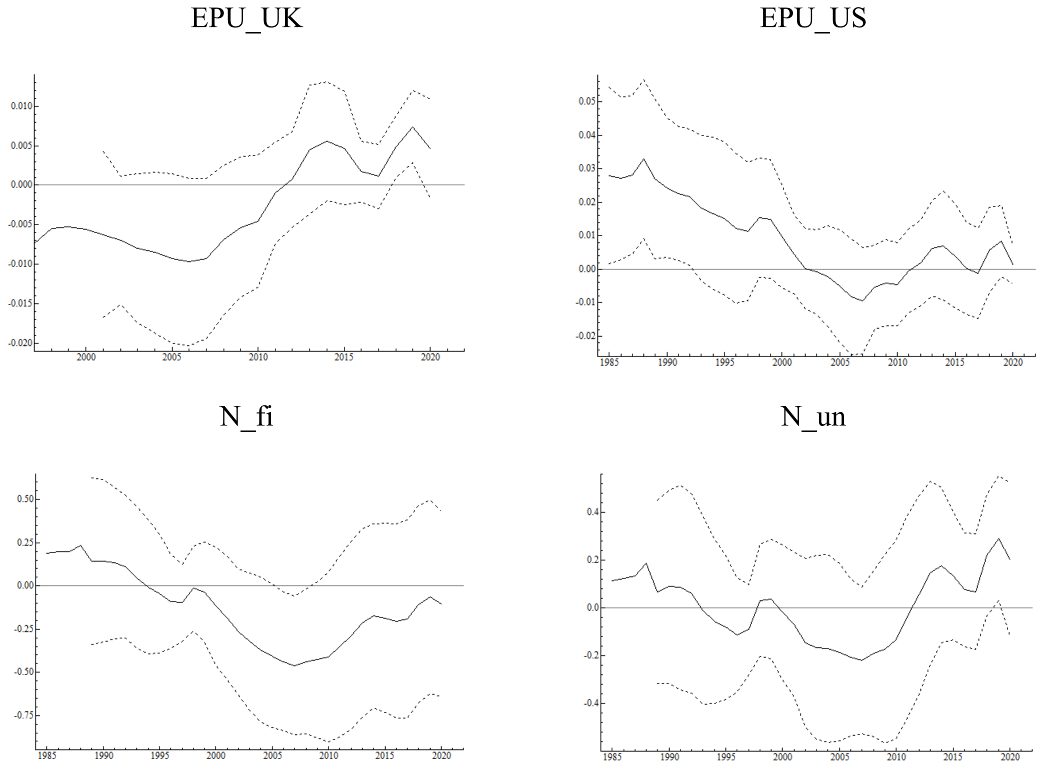
Note. Dashed lines denote the 95% confidence interval.

Figure 10. Time-varying parameters of economic uncertainty by gender (females)



Note. Dashed lines denote the 95% confidence interval.

Figure 11. Time-varying parameters of economic uncertainty by gender (males)



Note. Dashed lines denote the 95% confidence interval.

The evolution of the time-varying parameters and the results of the estimation of the state-space models by region are provided in Appendix 1. Finally, as an additional robustness check, in Appendix 2 we present the results of the Toda and Yamamoto (1995) test, confirming a significant effect of EPU_US, EPU_UK, and *DIS*_un in a large number of model specifications.

5. Conclusion

The present study has analysed the effect of different dimensions of economic uncertainty on suicide mortality in England, both by gender and at a regional level. Given that economic uncertainty has been proven to be a driver of the business cycle, we assessed the impact of three different dimensions of uncertainty: economic policy, financial, and labour market uncertainty. Uncertainty has been measured using both an index constructed by combining news-based text-mining measures of uncertainty both in the UK and the US, as well as a survey-based measure of disagreement and a Knightian uncertainty indicator.

First, we observed marked differences in the average suicide mortality by gender, while the differences across regions seemed minor. In this regard, it is worth noting that the male suicide rate is triple that of women in all regions. Notwithstanding, the relative dispersion of females' suicide rate doubles that of males.

Second, we assessed the long-run relationship between the six different proxies of uncertainty and suicide risk by means of a non-linear autoregressive distributed lag framework that allowed us to analyse the existence of potential asymmetries in the long-run nexus between both variables. Overall, we found that increased uncertainty was associated with increased suicide rates in the long-run, although its impact was greater in the case of decreases, especially for women. This result suggests that the incidence of sudden decreases in uncertainty are reflected in decreases in suicide rates among women. In this regard, we did not find major differences across regions.

When comparing the results according to the type of uncertainty proxy used, we found that the indicators of economic policy uncertainty and the indicator of financial uncertainty—measured by the degree of disagreement among consumers' financial expectations—were significant in six of the regions. The labour market uncertainty indicators for their part, were found to be significant in four of the regions with happen to be the ones with the highest unemployment rates. This finding somehow reveals the North-South divide and indicates the importance of assessing the different dimensions of economic uncertainty independently.

Finally, given the anticipatory nature of economic uncertainty and the obtained long-run relationship with suicide rates, these results confirm the usefulness of uncertainty indicators as tools for the early detection of increases in suicide risk and the design of suicide prevention programmes.

The present study is not without limitations. First, the results obtained may have been influenced by several biases derived from the measurement of suicide as well as the approximation of uncertainty. Second, given the length of the series, the study only focuses on a few of the factors affecting suicidal behaviour, which may give rise to additional potential biases. In the actual context, characterised by increasing uncertainty coming from different sources, a future line of research would be the evaluation of the incidence of other additional dimensions of economic uncertainty on the risk of suicide.

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Appendix 1

In this appendix, we present the results of the state-space analysis at a regional level. The state-space model is represented in equations 7 and 8 in Section 3. Table A1.1 contains the results of the optimal model specifications. Model selection was done by means of Akaike's information criterion. In accordance with the NARDL analysis, we test the standardised prediction errors using customary diagnostic tests. In all specifications, the error terms satisfy the assumption of homoskedasticity and are free of autocorrelation at the 5% significance level, so the details are not presented here for brevity. For all specifications, the error terms satisfy the assumption of homoskedasticity and are free of autocorrelation at the 5% significance level.

Figure A1.1 depicts the evolution of the significant time-varying uncertainty parameters at a regional level. As the graphs in Figure A1.1 suggest, overall regional results are in line with our baseline estimates contained in Figures 9 through 11. The impact of uncertainty shocks, regardless of the type, seem to be particularly driven by the recent pandemic. With only a few exceptions, we detected an intensification of this uncertainty effect in 2020.

Table A1.1 State-space model – Effect of uncertainty on suicide rates (by region)

Dependent variable	Uncertainty proxy	Parameters	
		Local level	X_t
North East	EPU_UK	21.900	-0.002
	EPU_US	13.885**	time-varying
	DIS_fi	20.400*	-3.297
	N_fi	18.655**	time-varying
	DIS_un	18.709*	-1.512
	N_un	17.515**	time-varying
North West	EPU_UK	21.323**	time-varying
	EPU_US	12.770	-0.004
	DIS_fi	8.876	-0.436
	N_fi	11.104**	time-varying
	DIS_un	7.340	0.522
	N_un	14.387**	time-varying
Yorkshire and the Humber	EPU_UK	17.393**	time-varying
	EPU_US	11.276	time-varying
	DIS_fi	6.693	-6.885
	N_fi	9.852	time-varying
	DIS_un	5.097	-0.708
	N_un	16.249**	time-varying

Notes. ** Significance at the 0.01 level, * at the 0.05 level.

Table A1.1 (cont.1) State-space model – Effect of uncertainty on suicide rates (by region)

Dependent variable	Uncertainty proxy	Parameters	
		Local level	X_t
East Midlands	EPU_UK	18.657**	time-varying
	EPU_US	16.750**	time-varying
	DIS_fi	21.170**	-7.526**
	N_fi	21.609**	time-varying
	DIS_un	17.092**	-1.615
	N_un	19.075**	time-varying
West Midlands	EPU_UK	14.399	-0.003
	EPU_US	15.552**	time-varying
	DIS_fi	21.803**	time-varying
	N_fi	23.288**	time-varying
	DIS_un	18.611*	-0.529
	N_un	20.314**	time-varying
East	EPU_UK	14.335**	time-varying
	EPU_US	8.857	time-varying
	DIS_fi	14.654*	-8.080*
	N_fi	13.845**	time-varying
	DIS_un	6.816	0.811
	N_un	21.468**	time-varying

Notes. ** Significance at the 0.01 level, * at the 0.05 level.

Table A1.1 (cont. 2) State-space model – Effect of uncertainty on suicide rates (by region)

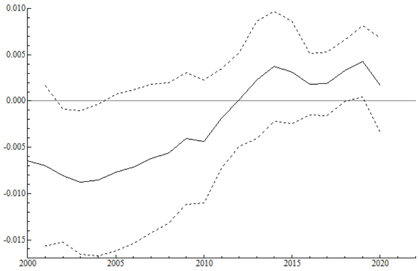
Dependent variable	Uncertainty proxy	Parameters	
		Local level	X_t
London	EPU_UK	19.256	0.003
	EPU_US	20.156**	time-varying
	DIS_fi	29.107**	-10.040**
	N_fi	35.714**	time-varying
	DIS_un	22.055*	-1.054
	N_un	29.187**	time-varying
South East	EPU_UK	12.196**	time-varying
	EPU_US	14.477**	time-varying
	DIS_fi	19.144**	-4.086
	N_fi	17.094**	time-varying
	DIS_un	21.254**	0.659
	N_un	19.369**	time-varying
South West	EPU_UK	15.269**	time-varying
	EPU_US	14.377**	time-varying
	DIS_fi	18.297**	-4.4020
	N_fi	14.790**	time-varying
	DIS_un	16.086**	0.4067
	N_un	15.685**	time-varying

Notes. ** Significance at the 0.01 level, * at the 0.05 level.

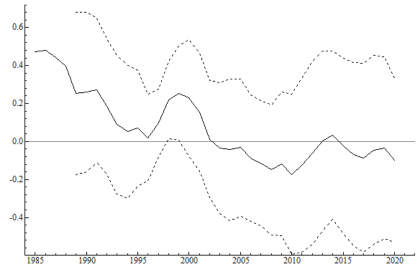
Figure A1.1. Time-varying parameters of economic uncertainty by region

North West

EPU_UK

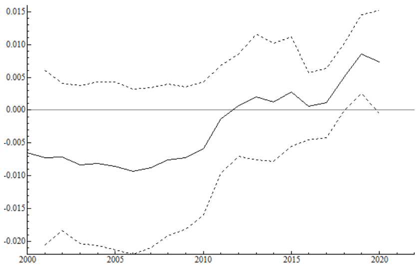


N_fi

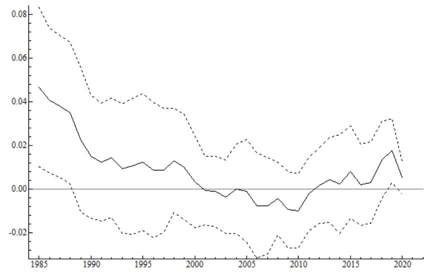


Yorkshire and the Humber

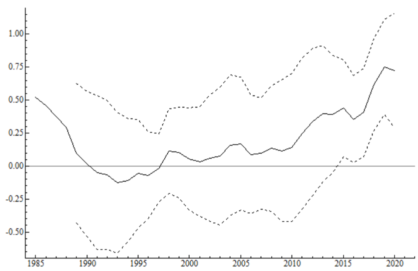
EPU_UK



EPU_US



N_un

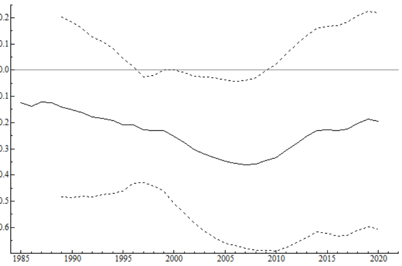


Note. Dashed lines denote the 95% confidence interval.

Figure A1.1. (cont.1) Time-varying parameters of economic uncertainty by region

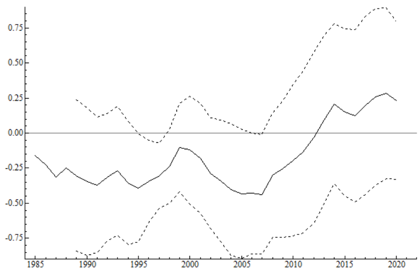
East midlands

N_fi

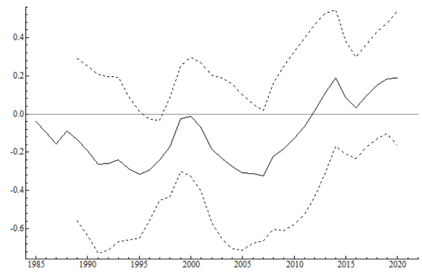


West Midlands

N_fi

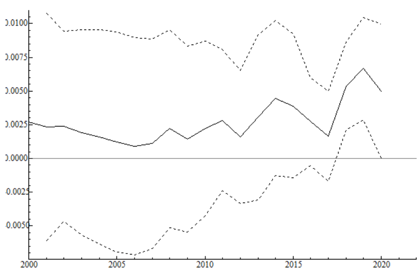


N_un



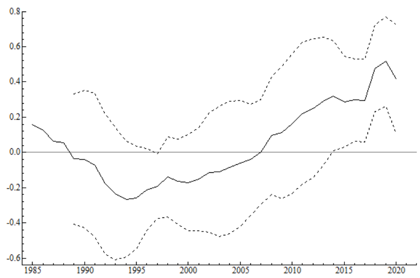
East

EPU_UK



EPU_US

N_un



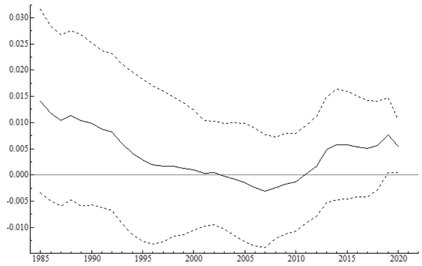
Note. Dashed lines denote the 95% confidence interval.

Figure A1.1. (cont.2) Time-varying parameters of economic uncertainty by region

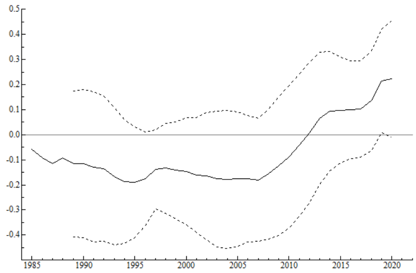
London

EPU_UK

EPU_US

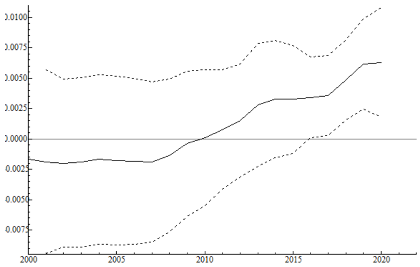


N_un



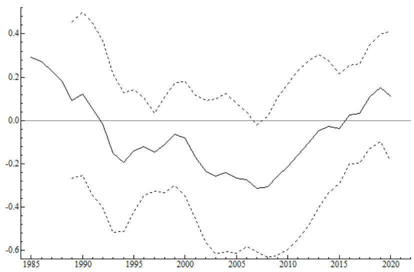
South West

EPU_UK



N_fi

N_un



Note. Dashed lines denote the 95% confidence interval.

Appendix 2

In this appendix we present the results of the Toda-Yamamoto test, which is based on a vector autoregression (VAR) model depicted through the following system of equations in matrix form:

$$Z_t = A_0 + A_1 Z_{t-1} + \cdots + A_p Z_{t-p} + \varepsilon_t \tag{A2.1}$$

where $Z_t = [SR\ X\ GDP\ UN]'$ is a 4x1 vector of system variables, X is the chosen uncertainty indicator, A_0 is a 4x1 vector of constant terms, $A_1 \ldots A_p$ are 4x4 matrices of parameters, and ε_t is a 4x1 white noise vector process. The lag order p of model (A2.1) is set by the Akaike information criterion.

Toda and Yamamoto's (1995) procedure properly accounts for mixed trending properties of the assessed variables—a mixture of I(0) and I(1) variables—. This is done by augmenting model (A2.1) by an additional lag of all variables. The added lags are not considered in the Granger-causality test procedure, i.e. in joint testing of all lags of a particular variable. The added lags are present in the models only to enable the asymptotic χ^2 distribution of the Wald test statistic used in the Granger-causality test. Results are presented in Table A2.1, both for England as a whole and by gender, and in Table A2.2 for the different regions.

Table A2.1 Toda and Yamamoto (1995) Granger causality test – Results for England (by gender)

Causality			
From	To	lags	p-value
EPU_UK	England	3	0.000
EPU_US		3	0.393
DIS_fi		1	0.130
N_fi		1	0.233
DIS_un		2	0.004
N_un		1	0.541
EPU_UK	England_f	3	0.000
EPU_US		2	0.053
DIS_fi		1	0.823
N_fi		1	0.124
DIS_un		1	0.016
N_un		1	0.567
EPU_UK	England_m	3	0.007
EPU_US		2	0.219
DIS_fi		1	0.090
N_fi		1	0.420
DIS_un		3	0.004
N_un		1	0.655

Table A2.2 Toda and Yamamoto (1995) Granger causality test – Results by region

Causality			
From	To	lags	p-value
Region 1			
EPU_UK	North East	3	0.004
EPU_US		2	0.000
DIS_fi		1	0.485
N_fi		2	0.757
DIS_un		2	0.014
N_un		1	0.995
Region 2			
EPU_UK	North West	3	0.712
EPU_US		2	0.592
DIS_fi		1	0.081
N_fi		2	0.608
DIS_un		1	0.267
N_un		1	0.625
Region 3			
EPU_UK	Yorkshire and the Humber	3	0.353
EPU_US		3	0.371
DIS_fi		1	0.667
N_fi		2	0.784
DIS_un		1	0.819
N_un		1	0.362

Table A2.2 (cont.1) Toda and Yamamoto (1995) Granger causality test – Results by region

Causality			
From	To	lags	p-value
Region 4			
EPU_UK	East Midlands	3	0.116
EPU_US		2	0.078
DIS_fi		1	0.022
N_fi		2	0.285
DIS_un		3	0.001
N_un		2	0.066
Region 5			
EPU_UK	West Midlands	3	0.201
EPU_US		3	0.137
DIS_fi		3	0.149
N_fi		1	0.543
DIS_un		3	0.010
N_un		2	0.177
Region 6			
EPU_UK	East	3	0.284
EPU_US		3	0.631
DIS_fi		3	0.800
N_fi		3	0.921
DIS_un		1	0.083
N_un		3	0.596

Table A2.2 (cont.2) Toda and Yamamoto (1995) Granger causality test – Results by region

Causality			
From	To	lags	p-value
Region 7			
EPU_UK	London	2	0.404
EPU_US		2	0.009
DIS_fi		3	0.005
N_fi		3	0.992
DIS_un		1	0.178
N_un		1	0.391
Region 8			
EPU_UK	South East	2	0.050
EPU_US		2	0.034
DIS_fi		2	0.271
N_fi		2	0.877
DIS_un		1	0.653
N_un		1	0.8502
Region 9			
EPU_UK	South West	2	0.007
EPU_US		2	0.278
DIS_fi		3	0.003
N_fi		2	0.555
DIS_un		1	0.405
N_un		3	0.133

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