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Economic activity and suicides: Causal evidence from macroeconomic shocks in England and Wales

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ABSTRACT

The relationship between economic activity and suicides has been the subject of much scrutiny, but the focus in the extant literature has been almost exclusively on estimating *associations* rather than *causal* effects. In this paper, using data from England and Wales between January 1, 1997 and December 31, 2017, we propose a plausible set of assumptions to estimate the *causal* impacts of well-known macroeconomic variables on the daily suicide rate. Our identification strategy relies on scheduled macroeconomic announcements and professional economic forecasts. An important advantage of using these variables to model suicide rates is that they can efficiently capture the elements of 'surprise or shock' via the observed difference between how the economy *actually* performed and how it was *expected* to perform. Provided that professional forecasts are unbiased and efficient, the estimated 'surprises or shocks' are 'as good as random', and therefore are exogenous. We employ time series regressions and present robust evidence that these exogenous macroeconomic shocks affect the suicide rate. Overall, our results are consistent with economic theory that shocks that reduce estimated permanent income, and therefore expected lifetime utility, can propel suicide rates. Specifically, at the population level, negative shocks to consumer confidence and house prices accelerate the suicide rate. However, there is evidence of behavioural heterogeneity between sexes, states of the economy, and levels of public trust in government. Negative shocks to the retail price index (RPI) raise the suicide rate for males. Negative shocks to the growth rate in gross domestic product (GDP) raise the population suicide rate when the economy is doing poorly. When public trust in government is low, increases in the unemployment rate increase the suicide rate for females.

1. Introduction

Suicide is a preventable global public health issue that claims 703,000 lives per year (WHO, 2021). Suicide is currently the fourth leading cause of death globally for adolescents and adults aged 15–29 and affects twice as many men than women. In England and Wales, in 2021, suicide was reportedly highest amongst working aged people between 45 and 54 (more severe for men than women. See Fig. 1). In a recent report, Baker (2022) finds that the suicide rate in the most deprived 10% of areas during 2017–2019 in England was 14.1 per 100, 000, which is almost double the rate of 7.4 in the least deprived decile. These facts, as well as prevailing discussions in the academic and policy circles (Berk et al., 2006; Claveria, 2022) on the causes and preventive measures of suicide, suggest that economic conditions can act as 'climate factors' to precipitate the risk of suicide. However, the substantive literature on the subject (which we will discuss shortly) appears to establish an *association*, rather than establishing a robust *causal* link, between economic activities and suicide, challenged primarily by finding the right source of exogenous variations of the causal instrument. In this paper, we propose a mechanism that helps identify an exogenous source of variations via macroeconomic announcements and professional forecasts. We use them to establish the *causal* effects of economic activities on suicide under a plausible set of assumptions.

Suicide is a complex outcome of the interaction among 'seed' factors, such as mental illness, 'soil' factors, such as the influence of major life events, and 'climate' factors, which include changes in economic conditions (Berk et al., 2006). However, it is often challenging to disentangle 'seed' from 'climate' factors, as mental instabilities can result

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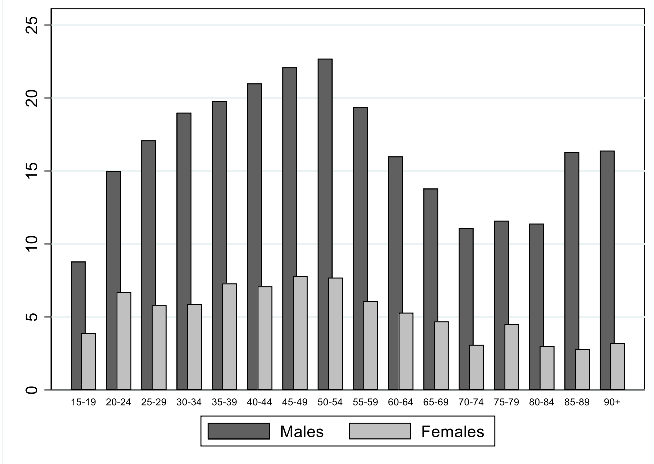

Fig. 1. Suicide rate per 100,000 in 2021 by sex and age group, England and Wales.
Source: ONS, Suicides in England and Wales tables, Table 5.

from regressive economic conditions, where deprived sections of a society would derive negative expectations of their future income stream. Among economic factors that are *associated with* the decision to commit suicide are unemployment (Morrell et al., 1993), economic recessions (Oyesanya et al., 2015), GDP growth (Agrrawal et al., 2017), inflation (Fountoulakis et al., 2014), consumer sentiment (Botha and Nguyen, 2022), economic policy uncertainty (Vandoros et al., 2019), and financial market fluctuations (Wisniewski et al., 2020). The methodological challenges of eliciting a reliable source of exogenous variations in these factors, which we will discuss in detail in Section 2.4, appear still significant in the extant studies.

Indeed, economic recessions and mediators such as unemployment, income decline, and unmanageable debts (captured broadly, for instance, via an aggregate index such as the global economic uncertainty index, as in Claveria (2022)) are significantly associated with poor mental well-being, increased rates of common mental disorders, substance-related disorders, and suicidal behaviours (Frasquilho et al., 2015; Martin-Carrasco et al., 2016). Based on data from Emergency Departments, recent unemployment is associated with increased risk of inflicting injury to partners (Kyriacou et al., 1999) whilst, during the mortgage market crisis, the number of domestic violence related hospitalisations increased (Medel-Herrero et al., 2020). This may be related to the level of acute stress experienced by the perpetrator (Bhalotra et al., 2021), which is also known to increase immediate voluntary alcohol consumption (De Goeij et al., 2015). Evidence from experimental studies confirms the relationship between economic crises, poor mental health and the risk of suicide. For example, a recent study by Christian et al. (2019) documented the effect of economic shocks, due to lack of rainfall on crop production, on mental health and the rate of suicides in Indonesia.

Many suicides happen impulsively during times of crisis (Rimkeviciene et al., 2015). They may progress from ideation to execution in a manner of hours or even minutes (Simon et al., 2001). While statistics on the proportion of such impulsive attempts vary wildly, some authors put it as high as 50% (Caceda et al., 2018) or even 80% (Kleespies et al., 2011). While the roles played by some calendar patterns, e.g. days of the week, holidays (Beauchamp et al., 2014), and environmental phenomena, e.g. temperature, air pollution (Heo et al., 2021; Page et al., 2007), have been studied, little is known about the short-term economic factors that may precipitate a decision to commit suicide. Public education and medical treatments should be focused on raising awareness and access to support amongst populations at higher risk. To better understand at risk groups, it is imperative that we examine the short-term economic factors that may trigger an ongoing decision to take one's own life or elicit an impulsive suicide attempt.

Furthermore, to the best of our knowledge, the question of *causality* has remained largely under-researched in this area, where current evidence is usually derived from time series or panel data analyses that estimate the *association* between the suicide rate (or suicide counts) and the economic factor(s) of interest. The limitation of previous studies is that, due to simultaneity and omitted variable biases, simply regressing the suicide rate on some economic factor(s) and a set of controls cannot produce unbiased and consistent estimates on the *causal* effects of the economic factors under observation. In this paper, we aim to estimate the *causal* relationships between six well-known macroeconomic indicators (GDP growth, retail sales, consumer confidence, house prices, unemployment rate, and the RPI) and suicidal behaviour under a plausible set of assumptions. (These indicators are defined in Panel B of Table 1.) By examining the impact of daily macroeconomic shocks, we can shed light on which economic factors may influence an individual's decision to commit suicide on a given day, thereby informing policies and programmes for suicide prevention.

2. Methods

2.1. Suicides data

We obtain a daily time series of the number of suicides in England and Wales from the Office for National Statistics (ONS). Since our data about macroeconomic shocks start from the beginning of January 1997 and the suicides data are available until the end of 2017, the sample period employed in the empirical analysis is from January 1, 1997 to December 31, 2017. Information about the sex of the victim is available starting from January 1, 2001. Mid-year population estimates, used to compute suicide rates, are from the Welsh government's website (https://statswales.gov.wales), and we linearly interpolate to obtain daily estimates.

2.2. Macroeconomic indicators and shocks

At regular intervals, private organisations and government agencies, such as the ONS (https://www.ons.gov.uk/), collect data and release statistics on the state of the UK economy. For example, once a month, the ONS releases information on the latest value of the unemployment rate to the public. Such announcements are scheduled in advance. The economics literature documents that investors in financial markets react to the surprises, or shocks, that they contain (Andersen et al., 2007). In line with this literature, we conjecture that the shock contained in a macroeconomic announcement is represented by the difference between the actual value taken by the macroeconomic indicator under observation (e.g. retail sales) and the value that had been expected by the public. Specifically, following Balduzzi et al. (2001), we measure a shock, S_{it}, to macroeconomic indicator i on day t as

$$S_{it} = \frac{A_{it} - F_{it}}{Std(A_i - F_i)} \tag{1}$$

where A_{it} represents the announced (i.e. actual) value of macroeconomic indicator i on day t, and F_{it} represents the value that the public had been expecting. The denominator in formula (1) normalises the shocks, or surprises, by dividing them by their sample standard deviation. This facilitates interpretation and ensures that the results can be compared directly across macroeconomic indicators.

An example can help clarify the logic behind formula (1). The following is an excerpt from an online article published by BBC News on November 16, 2006:

> "[Retail] sales jumped 0.9%, three times more than analysts forecast, and the biggest monthly gain since November 2005, the Office for National Statistics said."

Table 1
Summary statistics and variable definitions.

	count	mean	std	min	max	Definition
Panel A: Suicides						
Persons	7,670	13.481	3.935	2	31	
Males	6,209	10.043	3.363	1	28	
Females	6,209	3.243	1.825	0	12	
Panel B: Standardised macroeconomic shocks						
GDP	229	−0.098	1.000	−7.04	3.52	Growth rate in real gross domestic product (quarter-on-quarter), i.e. the market value of all finished goods and services produced over a period of time
Retail sales	251	0.218	1.000	−2.78	5.00	Growth rate in the volume of goods sold to the general public, excluding automotive fuel (month-over-month)
Consumer confidence	181	0.039	1.000	−2.61	3.73	Index measuring how optimistic households feel about the state of the economy and their personal finances, based on a survey
House prices	163	0.175	1.000	−3.31	3.98	Growth rate in Nationwide Building Society's house price index (month-over-month)
Unemployment rate	187	−0.128	1.000	−2.28	2.28	Number of individuals out of work who are actively looking for a job as a percentage of the economically active population
RPI	246	0.135	1.000	−3.12	4.37	Growth rate in the retail price index (month-over-month), which tracks the cost of a representative basket of retail goods and services
Panel C: Population (in 000s)						
Population	7,670	54675.78	2288.50	51486.06	58931.73	
Male population	7,670	26821.07	1240.53	25072.06	29119.05	
Female population	7,670	27854.70	1048.05	26414.01	29812.68	
Panel D: Control variables						
EPU	7,670	240.964	190.188	0.00	2660.72	Baker et al.'s (2016) economic policy uncertainty index for the UK. Daily values were available from 2001, and we estimated daily values between 1997 and 2000 by linear interpolation from monthly values. From https://www.policyuncertainty.com/
GPR	7,670	99.064	65.322	0.00	1045.60	Caldara and Iacoviello's (2022) global geopolitical risk index. From https://www.matteoiacoviello.com/gpr.htm
Misery	7,670	0.000	1.519	−2.28	4.03	Misery index, i.e. the sum of the z-scores of the unemployment rate and inflation rate (RPI) in the UK, as in Yang and Lester (1992). Both rates from https://www.ons.gov.uk/
Brent (%)	5,322	0.019	2.294	−19.89	18.13	Daily log return on crude oil (Europe Brent spot price FOB, USD per barrel). From https://www.eia.gov/
FTSE_All (%)	5,304	0.014	1.114	−8.71	8.81	Daily log return on the FTSE All-Share stock market index, representing about 98% of UK stock market capitalisation. From Bloomberg.
EffExchRate (%)	5,478	−0.002	0.434	−6.18	2.15	Daily log return on the nominal effective exchange rate index for the British pound (GBP), based on a basket of 60 economies' currencies. From https://www.bis.org/
FTSE_VIX	6,572	19.622	8.649	6.19	78.69	FTSE 100 volatility index, measuring the size of the fluctuations that investors expect in the UK stock market over the next 30 days. Available from 04/01/2000. On days when the market was closed (e.g. weekends), we estimated its values by linear interpolation. From Bloomberg.

Since retail sales measure the sales of goods and services to consumers, and more sales signal greater levels of economic activity, the above is an example of a *positive macroeconomic shock*. Analysts had forecast a +0.3% change (*F*) in retail sales for the period under observation, whereas the actual outcome turned out to be a more conspicuous +0.9% change (*A*). The non-normalised surprise, or forecast error, is equal to +0.6% (= *A* – *F*). In other words, the economy performed better than expected. Had the actual value of this macroeconomic indicator turned out to be, say, +0.1%, this would have represented a *negative macroeconomic shock*. Even if sales increased, their growth was less than projected.

We obtain the actual values (*A*) of all relevant UK macroeconomic indicators from Bloomberg, a major provider of economic data. As is common in the economics literature, as a proxy for *F,* we use the median forecasts of a sample of professional analysts, which we obtain from Bloomberg (Andersen et al., 2007). Analysts surveyed by Bloomberg typically submit their forecasts in the month preceding an announcement date, and Bloomberg publishes the resulting median during the week before the announcement (Chen et al., 2013). Since professional economic forecasts tend to reach the public via the mass media, we assume that, just before a scheduled announcement occurs, the public's expectations are in line with those of the "experts" (Mackuen et al., 1992).

We also conjecture that, unlike professional investors, the general public is likely to pay attention only to the most consequential economic metrics that have an impact on their own lives. This raises the question: which macroeconomic indicators matter the most to a layperson? To address this matter, we assume that public attention and media coverage go hand in hand, and consequently we employ the latter as a proxy for the former. Using the procedure described in Section A.1 of the online Appendix, we find that GDP, retail sales, consumer confidence, house prices, the unemployment rate, and the RPI are the indicators that receive the greatest amount of attention from news media in the UK. Consequently, we choose to focus on them in our analysis.

2.3. Hypothesis development

While economic factors are by no means the only driving forces behind suicidal behaviour, a stream of the literature contends that a portion of the variation in suicide rates can be attributed to economic variables. Hamermesh and Soss (1974) are the first to model the decision as to whether and when to commit suicide as a rational decision involving economic benefits and costs. Their approach relies on standard economic theory within the discounted lifetime utility framework. Specifically, they posit that the typical individual of age *m* derives utility (*U*) from consumption (*C*), which is a function of age and real permanent income (Y_p). The individual also derives disutility from the cost (*K*) of maintaining his health at an acceptable level, which is assumed to increase with age. Mathematically:

$$U_m = U\left[C(m, Y_p) - K(m)\right] \tag{2}$$

Therefore, the present value of the typical individual's expected lifetime utility at age α is

$$Z(\alpha, Y_p) = \int_{\alpha}^{\omega} e^{-r(m-\alpha)} U_m P(m)\, dm \tag{3}$$

where *P(m)* represents the probability that the individual will survive to age *m* having survived to age α, *r* is the rate at which the individual discounts future utility, and ω represents the maximum attainable age.

The key assumption in the model is that individual *i* takes his own life when

$$Z_i(\alpha, Y_p) < b_i \tag{4}$$

In other words, the individual commits suicide when the present value of his expected lifetime utility, $Z_i(\alpha, Y_p)$, falls below a given threshold that can be interpreted as his "distaste for suicide", b_i. The latter is an individual-specific parameter, and it can be used to capture, for example, demographic heterogeneity in suicide rates (e.g. males vs. females).

While "the concept of permanent income [Y_p] is [...] hard to define precisely" (Friedman, 1957), economists typically interpret it roughly as lifetime income or wealth. Since higher permanent income, Y_p, implies more consumption and, therefore, greater discounted lifetime utility ($\partial Z/\partial Y_p > 0$), the model predicts, as Hamermesh and Soss (1974) show, that the suicide rate is a decreasing function of permanent income. As such, this model can be used to analyse the impact on population suicide rates of any economic factors that may affect the permanent incomes of a large portion of the population. For instance, Wisniewski et al. (2020) examine the association between stock market fluctuations and suicides in a sample of 36 countries based on the assumption that the former is a determinant of permanent income.

Following an analogous line of reasoning, we conjecture that shocks to the six macroeconomic indicators in our sample affect people's estimated permanent incomes and, in turn, the suicide rate. This allows us to derive a set of testable hypotheses. (The analytical derivations are presented in section A.2 of the online Appendix.) Broadly, the hypotheses can be summarised as follows:

H1. There exists a negative relation between GDP growth, consumer confidence, house prices, retail sales and the suicide rate.

H2. There exists a positive relation between the unemployment rate and the suicide rate.

H3. There exists a positive (negative) relation between RPI and the suicide rate.

2.4. Model on suicide rate: identifying an exogenous source of variations

Our goal is to test the hypotheses and estimate, under a plausible set of assumptions, the *causal* impact on the suicide rate of the six macroeconomic factors. To achieve this, it is necessary to identify *plausibly exogenous sources of variation* in their values. In other words, the values of these indicators must be determined independently of other factors that may affect the suicide rate in a given time period. Simply regressing the suicide rate on the actual values (A) of these indicators would produce biased and inconsistent estimators of their causal effects due to omitted variable bias and simultaneity bias (Wooldridge, 2015). To circumvent these problems, we employ the following model:

$$SuicideRate_t = \alpha + \sum_{i=1}^{6} \beta_i S_{it} \times I_{it} + x_t' \gamma + \sum_{k=1}^{n} \varphi_k SuicideRate_{t-k} + \varepsilon_t \tag{5}$$

where $SuicideRate_t$ measures the suicide rate per 100,000 persons in England and Wales on day t, S_{it} measures the shock to macroeconomic indicator i on day t, and I_{it} is an indicator variable that takes the value of 1 if data about indicator i are announced on day t, and 0 otherwise.

According to formula (1), the sign and the size of a macroeconomic shock depend on the difference between how the economy *actually* performed and how it was *expected* to perform. Our identification strategy relies on the intuition that, if professional economic forecasts (F) are unbiased and efficient, then the forecast errors ($S = A$ - F), or shocks, are "as good as random" (Card and Dahl, 2011). And if the shocks are as good as random, then they are assigned independently of any other unobservable factors that may determine the suicide rate on day t and end up in the error term, ε_t. Furthermore, as both A and F are determined prior to the announcement date t, they cannot be affected by suicides occurring on day t (reverse causation). Therefore, the zero conditional mean assumption, $E[\varepsilon|S, \boldsymbol{x}] = E[\varepsilon] = 0$, is satisfied (Wooldridge, 2015). In econometric terms, S_i is an exogenous variable. Under the assumptions mentioned above, the implication is that specification (5) can generate unbiased estimators of the *causal* effects of changes in the six macroeconomic indicators under observation.

While adding control variables to equation (5) is not necessary to identify these causal effects, to increase the efficiency of our estimators we add a vector of controls, $\boldsymbol{x}_t$. These consist of a linear time trend, seasonalities (holiday, day-of-the-week, and month-of-the-year dummies), and other variables inspired by the findings of previous studies (see Panel D of Table 1 for the list of variables and their definitions). We also add n lags of the dependent variable, where k denotes the lag and n is selected based on the Bayesian Information Criterion (BIC).

A natural question is whether macroeconomic shocks only have a contemporaneous effect on suicidal behaviour or they also influence the decision to take one's own life with a lag. To address this matter, we re-estimate equation (5) but with lags of each macroeconomic surprise indicator, S_i. We also consider the potential effects of *cumulative* shocks. Specifically, we re-estimate equation (5) with the addition of the explanatory variable *Cumulative_*S_i, which measures the sum of the shocks to macroeconomic indicator i over the previous 3–6 months.

2.5. Time-varying responses based on the state of the economy

Several studies find that the way investors in financial markets react to macroeconomic shocks depends on the state of the economy (Boyd et al., 2005; McQueen and Roley, 1993). We conjecture that a similar mechanism may be at play regarding suicidal behaviour among the general population: A negative piece of news during a period when the economy is performing well is more likely to be viewed with detachment, while negative news during a period of poor economic activity is more likely to lead to despair.

To investigate this hypothesis, we employ the misery index, i.e. the sum of the standardised unemployment and inflation rates in the UK (Yang and Lester, 1992), as a proxy for the state of the economy (Lee et al., 2007). High-misery periods signal that the economy has been doing poorly, while low-misery periods indicate that economy activity has been thriving. Specifically, we construct a dummy variable, *High_misery*, that takes the value of 1 when the misery index is above its sample median, and 0 otherwise. We then re-estimate equation (5) after adding to the right-hand side *High_misery* and interactions between *High_misery* and each S_i.

3. Empirical results

Panel A of Table 1 provides some summary statistics, and Figure A1 in the online Appendix displays the frequency distribution of daily suicides by sex. Summary statistics on the shocks experienced by the six indicators, as computed by formula (1), are displayed in Panel B of Table 1. On the average day, about 10 men and 3 women commit suicide. The total number of suicides varies between a minimum of 2 and a maximum of 31 per day. Overall, these statistics are in line with the findings of previous studies that focus on the same geographical area (Vandoros et al., 2019).

Since, in much of the analysis, our dependent variable measures the daily suicide rate per 100,000 persons, in Panel C of Table 1 we also display summary statistics on the size of the population in England and Wales. Figure A2 in the online Appendix displays the frequency distribution of shocks for each of the six indicators.

Before estimating equation (5), we find it useful to examine the quality of the sample of professional forecasts at our disposal. To do so, we run a set of unbiasedness, efficiency, and randomness tests (see Section A.3 in the online Appendix). The results reveal that the forecast errors (or shocks) concerning GDP growth, consumer confidence, and the unemployment rate pass all three quality tests with a clean bill, and we can be quite confident that they are "as good as random". The shocks to house prices and RPI pass some of the tests. The shocks to retail sales raise more concerns, and we are less confident in their randomness. For this reason, while we conduct our main analysis using the shocks measured by formula (1), in Section A.9 of the online appendix we discuss some robustness tests that we run after debiasing the shocks to retail sales, house prices, and RPI, and we show that, with the exception of the effects of retail sales, our main findings are robust.

3.1. Baseline specification

A set of (untabulated) augmented Dickey-Fuller tests rejects the null hypothesis of a unit root at the 1% level for all but one of the continuous variables in model (5): *Misery*. We believe that the non-stationarity of the misery index is of no consequence in this study because, as we show later in Table 2, the inclusion/exclusion of this variable has no material impact on our results.

We estimate equation (5) by OLS and compute Newey and West (1987) standard errors with a lag truncation parameter of $T^{1/4}$ (T = number of observations), which are robust to heteroscedasticity and autocorrelation in the error term. The output is displayed in Table 2.

The analysis begins with a stripped-down specification that contains only the macroeconomic shocks, S_i (column 1), leading to *finding 1; consistent with hypotheses H1-H2, the signs of the coefficients on GDP, retail sales, consumer confidence, and house prices are negative, and the coefficient on the unemployment rate is positive. In other words, negative shocks to the aforementioned cause a contemporaneous increase in the daily suicide rate.* However, only the coefficients on retail sales, consumer confidence, and house prices are statistically significant at conventional levels. The coefficient on RPI is negative but statistically insignificant.

In columns 2–6, we gradually add a set of variables to control for a linear time trend, seasonal patterns in suicides, and daily economic/geopolitical factors that may influence individuals' well-being and suicidal behaviour. The overall fit of the model (adjusted R^2) increases with the addition of the controls, but the key results remain qualitatively unchanged.

To assess the extent to which the causal effects of macroeconomic shocks are practically meaningful, it is useful to transform suicide rates into suicide counts. According to the estimates in column 6 of Table 2, a negative one-standard-deviation surprise in the house price index increases the daily suicide rate by 0.00123. Since the sample average population in England and Wales is 54,675,780 (see Table 1), this is equivalent to an additional 0.67 suicides per day (=0.00123 ÷ 100,000 × 54,675,780). Relative to the sample mean daily suicide count (13.481), this represents a 4.97% increase. Similar to the effect of the house price index on the daily suicide rate, the effects of shocks to consumer confidence and retail sales are of the same order of magnitude.

It is worth noting that there is no near-multicollinearity among the macroeconomic surprise indicators, S_i's, in equation (5) (see Section A.4 in the online Appendix). Furthermore, imposing alternative time trends or replacing the original dependent variable with a measure of the abnormal daily suicide rate (= suicide rate on day t minus a 2-year moving average of the suicide rate) has no material impact on the main results (see Section A.5 in the online Appendix). Analogously, when we model the daily suicide count using a log-linear model or static and dynamic count-data models, we find that our results are robust (see Section A.6 in the online Appendix).

While equation (5) is concerned with contemporaneous effects, we also investigate whether macroeconomic shocks have lagged effects. We find no evidence that individual shocks exert lagged effects on suicidal behaviour. However, when we examine the effect of *cumulative* shocks, we find a statistically significant relationship between the suicide rate on day t and the sum of the shocks that house prices experienced during the previous 3–6 months. Namely, the more negative the sum of past shocks, the greater the increase in the suicide rate (see Section A.7 in the online Appendix).

Lastly, since analyst forecasts concerning house prices, RPI, and retail sales do not fully pass our unbiasedness and efficiency tests, we also re-estimate equation (5) after debiasing the corresponding shocks (see Section A.9 in the online Appendix). The results indicate that our findings are robust, with the exception of the effects of retail sales.

Table 2
Baseline specification.

	Hypothesis	Dependent variable: Daily suicide rate per 100,000 people					
		(1)	(2)	(3)	(4)	(5)	(6)
GDP	–	−0.000699 (−1.43)	−0.000624 (−1.33)	−0.000603 (−1.29)	−0.000584 (−1.24)	−0.000595 (−1.25)	−0.000601 (−1.25)
Retail sales	–	−0.00107*** (−2.70)	−0.000863** (−2.29)	−0.000854** (−2.26)	−0.000825** (−2.16)	−0.000731* (−1.93)	−0.000717* (−1.88)
Consumer confidence	–	−0.00112** (−2.06)	−0.00112** (−2.06)	−0.00115** (−2.12)	−0.00115** (−2.13)	−0.00112** (−2.07)	−0.00114** (−2.11)
House prices	–	−0.00137*** (−3.18)	−0.00125*** (−3.00)	−0.00122*** (−2.98)	−0.00123*** (−3.03)	−0.00121*** (−2.94)	−0.00123*** (−3.01)
Unemployment rate	+	0.000364 (0.72)	0.000175 (0.36)	0.000238 (0.48)	0.000242 (0.49)	0.000269 (0.54)	0.000296 (0.60)
RPI	+/−	−0.000533 (−1.25)	−0.000646 (−1.55)	−0.000636 (−1.53)	−0.000623 (−1.50)	−0.000727* (−1.66)	−0.000716 (−1.63)
Linear time trend		No	Yes	Yes	Yes	Yes	Yes
Seasonalities		No	Yes	Yes	Yes	Yes	Yes
ln(EPU) & ln(GPR)		No	No	Yes	Yes	Yes	Yes
Misery		No	No	Yes	Yes	Yes	Yes
Financial market returns		No	No	No	Yes	Yes	Yes
ln(FTSE_VIX)		No	No	No	No	Yes	Yes
Lags of dep. variable		No	No	No	No	No	Yes
N		7670	7670	7670	7670	6572	6572
Adj. R^2		0.002	0.095	0.104	0.104	0.080	0.081

Notes: Seasonalities consist of holiday, day-of-the-week, and month-of-the-year dummy variables. *EPU*, *GPR*, and *FTSE*_VIX enter the regressions in logarithmic form (1 is added to *EPU* and *GPR* before taking the logarithm because their values contain some zeros). Since *EPU's* daily values are estimated by linear interpolation from monthly values until December 31, 2000, the coefficient on ln(*EPU*) is allowed to vary between 1997-2000 and 2001–2017 by means of an interaction with a dummy variable taking the value of 0 before January 1, 2001, and 1 thereafter. Financial market returns consist of *Brent*, *FTSE_ALL*, and *EffExchRate*; each of these three variables is interacted with an indicator variable that takes the value of 1 when the market is open (and consequently a return is observed), and 0 otherwise. The number of lags of the dependent variable included in the model is based on BIC. See Table 1 for variable definitions. t statistics in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

3.2. Analysis by sex and state of the economy

The summary statistics in Table 1 show that, while males represent about half of the population, the number of male suicides is about three times as large as that of females. To examine whether the impact of macroeconomic shocks on suicidal behaviour varies between males and females, we re-estimate equation (5) separately for each of the two groups.

The estimates for the male population are displayed in Table 3. The set of controls included in the regression varies across columns 1–6 just like in Table 2, but the results are, to a very large extent, robust. *This leads to finding 2: a negative surprise in the RPI increases the male suicide rate. No evidence of an impact is present for the remaining macroeconomic indicators.* According to the estimates in column 6, a negative one-standard deviation surprise in the RPI raises the male suicide rate by 0.0018, which, based on the sample average male population, is equivalent to an extra 0.48 male suicides (=0.0018 ÷ 100,000 × 26,821,070) per day. Relative to the sample mean male suicide count (10.043 per day), this represents a 4.78% increase. As explained in Section A.2 of the online appendix, state pensions in the UK were pegged to the RPI for the majority of the sample period. As such, the sign of this effect is consistent with the interpretation that, conditional on the inflation experienced by older households (i.e. pensioner inflation), a surprise drop in the RPI represents an expected income drop in real terms. *From this perspective, the negative relation between RPI shocks and male suicides is therefore consistent with hypothesis H3 and Hamermesh and Soss's (*1974*) economic theory of suicide.*

The estimates for the female population are displayed in Table 4. *What emerges is that, (Finding 3) consistent with hypothesis H1, negative shocks to consumer confidence and house prices raise the female suicide rate. No evidence of an effect is present for the remaining macroeconomic indicators.* According to the estimates in column 6, a negative one-standard deviation surprise in the house price index raises the female suicide rate by 0.00128, which is equivalent to an extra 0.36 female suicides (=0.00128 ÷ 100,000 × 27,854,700) per day. Analogously, a negative one-standard deviation surprise in consumer confidence raises the female suicide rate by 0.00121, which is equivalent to an extra 0.34 female suicides per day. Relative to the sample mean female suicide count (3.243 per day), these two effects amount to an 11.10% and 10.48% increase, respectively. In summary, we find evidence that the response of suicidal behaviour to macroeconomic shocks varies between sexes (*finding 4*).

The left chart in Fig. 2 displays the point estimates and 95% and 90% confidence intervals of the coefficients on S_i by misery state. The estimates are further broken down by sex in the middle and right charts of the figure. (Note that the list of control variables is the same as in column 6 of Table 2, with the exclusion of the misery index.) For the general population, consistent with hypothesis *H1*, negative house price shocks raise the daily suicide rate both in good and bad economic times. A meaningful result is that negative shocks to GDP growth raise the suicide rate, but only in bad economic times is there evidence of this effect. Negative shocks to retail sales increase the suicide rate, but evidence of this effect is present only in bad economic times. (As mentioned earlier, our estimates of the effects of retail sales should be treated with caution because, as shown in Section A.9 of the online Appendix, they are not robust to debiasing the forecast errors.) And negative shocks to consumer confidence raise the suicide rate, but only in good economic times do we find statistical evidence of this effect. *This can be summarised as finding 5: there is evidence that the response of suicidal behaviour to macroeconomic shocks depends on the state of the economy. Specifically, only in bad (good) economic times do we find evidence that shocks to GDP growth (consumer confidence) have an immediate effect on the population suicide rate.*

Breaking down the results further by sex, we find evidence only among males that GDP growth (*H1*) and RPI (*H3*) shocks affect the suicide rate, while evidence in support of the effect of house price shocks (*H1*) is present only among females. Consumer confidence shocks (*H1*) seem to affect both sexes, but only in good economic times do we find statistical evidence of an impact.

In a further test, we also examine whether the response of the suicide rate to macroeconomic shocks varies depending on the state of public trust in government, and we find evidence that this is indeed the case (see Section A.8 in the online Appendix). While the resulting pattern of coefficients is similar to that in Fig. 2, one of the results that deserve attention concerns the effect of shocks to the unemployment rate: We find that, when public trust in government is low, surprise increases in the unemployment rate raise the suicide rate for females.

4. Discussion

To advance the literature on the relationship between macroeconomics and suicides, we use data to examine the effect of *macroeconomic surprises*, including changes to GDP growth, retail sales, consumer confidence, house prices, unemployment rate, and the RPI, on the daily incidence of suicides in England and Wales from 1997 to 2017. To the best of our knowledge, this is the first time the *causal effect* of

Table 3
Male suicide rate.

	Hypothesis	Dependent variable: Daily suicide rate per 100,000 males					
		(1)	(2)	(3)	(4)	(5)	(6)
GDP	–	−0.00122 (−1.48)	−0.00110 (−1.32)	−0.00109 (−1.30)	−0.00100 (−1.19)	−0.00103 (−1.22)	−0.00101 (−1.20)
Retail sales	–	−0.00127* (−1.74)	−0.00100 (−1.42)	−0.000960 (−1.36)	−0.000879 (−1.23)	−0.000850 (−1.19)	−0.000813 (−1.14)
Consumer confidence	–	−0.000885 (−0.91)	−0.00101 (−1.05)	−0.00102 (−1.06)	−0.00106 (−1.10)	−0.00104 (−1.08)	−0.00107 (−1.11)
House prices	–	−0.00125 (−1.58)	−0.00114 (−1.48)	−0.00113 (−1.47)	−0.00114 (−1.49)	−0.00112 (−1.46)	−0.00115 (−1.51)
Unemployment rate	+	0.000148 (0.17)	0.000137 (0.16)	0.000141 (0.16)	0.000147 (0.17)	0.000150 (0.17)	0.000185 (0.21)
RPI	+/−	−0.00153* (−1.84)	−0.00185** (−2.28)	−0.00190** (−2.34)	−0.00186** (−2.29)	−0.00184** (−2.26)	−0.00180** (−2.21)
Linear time trend		No	Yes	Yes	Yes	Yes	Yes
Seasonalities		No	Yes	Yes	Yes	Yes	Yes
ln(EPU) & ln(GPR)		No	No	Yes	Yes	Yes	Yes
Misery		No	No	Yes	Yes	Yes	Yes
Financial market returns		No	No	No	Yes	Yes	Yes
ln(FTSE_VIX)		No	No	No	No	Yes	Yes
Lags of dep. variable		No	No	No	No	No	Yes
N		6209	6209	6209	6209	6209	6208
Adj. R^2		0.001	0.051	0.052	0.052	0.052	0.053

Notes: t statistics in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Female suicide rate.

	Hypothesis	Dependent variable: Daily suicide rate per 100,000 females					
		(1)	(2)	(3)	(4)	(5)	(6)
GDP	–	−0.000178 (−0.44)	−0.000180 (−0.45)	−0.000181 (−0.46)	−0.000213 (−0.54)	−0.000230 (−0.58)	−0.000239 (−0.60)
Retail sales	–	−0.000647 (−1.59)	−0.000601 (−1.48)	−0.000598 (−1.48)	−0.000622 (−1.53)	−0.000603 (−1.48)	−0.000604 (−1.48)
Consumer confidence	–	−0.00131*** (−2.82)	−0.00122*** (−2.66)	−0.00123*** (−2.67)	−0.00122*** (−2.66)	−0.00121*** (−2.63)	−0.00121*** (−2.63)
House prices	–	−0.00126*** (−3.33)	−0.00125*** (−3.23)	−0.00128*** (−3.30)	−0.00129*** (−3.33)	−0.00128*** (−3.33)	−0.00128*** (−3.33)
Unemployment rate	+	0.000419 (0.94)	0.000356 (0.79)	0.000378 (0.84)	0.000387 (0.85)	0.000389 (0.86)	0.000392 (0.86)
RPI	+/−	0.000141 (0.34)	0.000173 (0.41)	0.000182 (0.43)	0.000166 (0.39)	0.000175 (0.41)	0.000172 (0.41)
Linear time trend		No	Yes	Yes	Yes	Yes	Yes
Seasonalities		No	Yes	Yes	Yes	Yes	Yes
ln(EPU) & ln(GPR)		No	No	Yes	Yes	Yes	Yes
Misery		No	No	Yes	Yes	Yes	Yes
Financial market returns		No	No	No	Yes	Yes	Yes
ln(FTSE_VIX)		No	No	No	No	Yes	Yes
Lags of dep. variable		No	No	No	No	No	Yes
N		6209	6209	6209	6209	6209	6208
Adj. R^2		0.002	0.026	0.029	0.029	0.029	0.029

Notes: *t* statistics in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

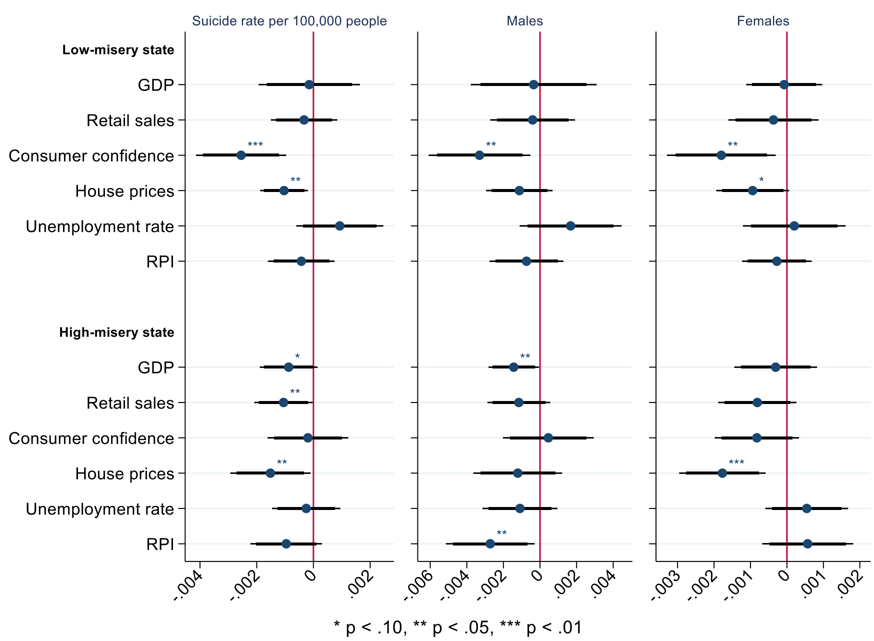

Fig. 2. Time-varying responses based on the state of the economy.

macroeconomic surprises on suicide has been described. In this regard, our findings can be compared and contrasted against the previous literature on macroeconomics, suicide and their *associations*.

Several pertinent findings emerge from our empirical analysis. Our results suggest that, at the population level, negative shocks to consumer confidence and house prices cause an immediate increase in the daily suicide rate. We also find that, under certain conditions and for certain groups (i.e. males or females), decreases in GDP growth or the RPI and increases in the unemployment rate raise the suicide rate. These effects are consistent with Hamermesh and Soss's (1974) economic theory of suicide. In this theory, shocks that reduce an individual's estimated permanent income, and therefore their expected lifetime utility, are found to increase suicides.

We find evidence of behavioural heterogeneity between sexes, which is consistent with prior research (Coope et al., 2014). In our study, at the aggregate level, the male suicide rate responds to changes in the RPI, while the female suicide rate responds to changes in consumer confidence and house prices. The latter result is consistent with a previous study, and the only known study, examining the *causal* relationship between consumer sentiment and suicides in the US. Although their methodology is different, their results are consistent with ours: as consumer sentiment decreases, the suicide rate increases, and this effect is stronger for females (Collins et al., 2021).

When the data are broken down by state of the economy, only in bad economic times do we find evidence that negative shocks to GDP growth raise the suicide rate, and the result is mainly driven by male suicides. The condition of 'in bad economic times' could explain why GDP per capita was not found to have an effect on suicide risk in a recent study in Japan (Okada et al., 2020). In our study, negative shocks to consumer confidence raise the suicide rate only during good economic times. This applies to both males and females. Negative shocks to house prices raise the suicide rate both in good and bad economic times, and the result is mainly driven by female suicides.

Lastly, we also find evidence that the response of suicidal behaviour to macroeconomic shocks varies depending on the level of public trust in government, a finding that is consistent with the documented association between trust in government and mental health (Choi et al., 2023). One of the results that deserve attention is that only in the low-trust regime is there evidence that surprise increases in the unemployment rate raise the suicide rate for females.

While our analysis focuses on suicides, to put things in perspective, it is worth noting that successful suicides are only the tip of the iceberg. For instance, Weber et al. (2013) find that "[t]here are nearly 25 suicide attempts for each suicide", though estimates in the literature tend to vary between 10 to 1 and 40 to 1 (Miller et al., 2012). According to UK survey data, the ratio of suicide ideations to suicides is 200 to 1 (Gunnell et al., 2004). Extrapolating these figures to the present context suggests that a negative one-standard-deviation surprise in house prices leads to about 17 suicide attempts ($=0.67 \times 25$) and 134 suicide ideations ($=0.67 \times 200$) per day. This leads us to conclude that the impact of macroeconomic shocks on suicidal behaviour and suicidal thoughts is practically significant.

While most of the existing economics and public health literatures focus on the correlations (or associations) between economic factors and suicidal behaviour, we contribute to our understanding of their relation by quantifying causal effects under a plausible set of assumptions. We employ multiple modelling approaches (classical linear regression, static and dynamic count-data models) and show that our key results are robust to alternative methodological assumptions. We employ a large set of controls (calendar effects, dynamics of financial markets, economic policy uncertainty, geopolitical risk) that ensure the efficiency of our estimators. The sizes of the effects that we detect are practically meaningful: a one-standard-deviation surprise change in one of the macroeconomic indicators in our sample leads to a contemporaneous increase in the daily suicide count of between 4.8% and 11.1% relative to its sample average.

There are a few limitations. First, though we also consider the effects of cumulative shocks, our methodology and the time frequency of our data are geared towards detecting the *immediate*, i.e. short-term, effects of changing economic conditions on suicidal behaviour. Second, different segments of the population may have different degrees of exposure to the consequences of changing economic conditions. As our data are aggregated at the country level, we cannot estimate treatment effects for various sub-populations of interest, and we are unable to shed light on the potential moderating roles played by factors such as age, geographical location, income, job security, home ownership, social networks, and the like. Analogously, individual characteristics such as propensity to depression and risk-taking behaviour might act as moderators or mediators, but they are unobservable based on our dataset, and consequently our analysis is mute on this point. Third, we cannot observe the extent to which the public pays attention to macroeconomic announcements, nor can we observe the public's expectations about the macroeconomic indicators in our sample. When estimating exogenous macroeconomic shocks, our methodology relies on a proxy for public attention, i.e. media coverage, and a proxy for the public's expectations, i.e. professional analysts' forecasts. It seems reasonable to conjecture that a large segment of society is exposed to information (i.e. announcements and professional forecasts) about the macroeconomic indicators that are most widely covered by the news media. Nevertheless, it is possible that some of the individuals at risk of suicide or who died by suicide in our sample were unaware of this information or held expectations that significantly differed from those of the experts. Fourth, while we show that there is variation between sexes in how suicidal behaviour responds to economic shocks, our study is mute on the factors that may drive these heterogeneous reactions. And while all the effects that we detect are consistent with Hamermesh and Soss's (1974) economic theory of suicide, our analysis cannot explain why some macroeconomic indicators appear to be more important than others in driving suicidal behaviour. We leave it to future research to shed light on these issues. Lastly, the estimated causal effect of shocks to retail sales is not fully robust to the way the shocks are measured, and therefore the causal effect of retail sales on suicide should be interpreted with caution.

Due to their effect on suicide rate, macroeconomics can have a devastating impact on society. These findings have implications for policymakers, where policies have the potential to mitigate the relationship between macroeconomics and suicide (Shand et al., 2022). To inform intervention design and delivery, further evidence is necessary to understand how suicidal ideation following an economic announcement may result in an attempt on one's life. Several interventions, such as 'job club' interventions, can reduce depressive symptoms in high risk, unemployed people (Vuori and Vinokur, 2005). Similarly, an inverse relationship between financial support and suicide mortality was observed in Japan, suggesting that funding support should be responsive, particularly during bad economic times (Okada et al., 2020). Social media can play a powerful role in reducing the impact of negative economic announcements. In line with the clinical literature on help-seeking behaviour, the internet can act as a gateway to formal mental healthcare for at risk individuals, linking them to social care and wider financial support. Following public announcements on the state of the economy, pro-help-seeking messages can be broadcasted through social media outlets. By using tailor-made algorithms and the underlying structure of social media networks, internet-based interventions can increase their reach and engage at risk individuals, respectively (Notredame et al., 2018).

CRediT authorship contribution statement

Gabriele M. Lepori: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Sara Morgan:** Conceptualization, Writing - original draft. **Borna A. Assarian:** Writing - original draft. **Tapas Mishra:** Writing - original draft, Writing - review & editing.

Declaration of competing interest

None.

Data availability

The data on suicide counts are freely available from the UK's ONS. Professional macroeconomic forecasts are available from Bloomberg upon subscription, and we do not have permission to share them.

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Appendix A. Supplementary data

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