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

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Online Appendix

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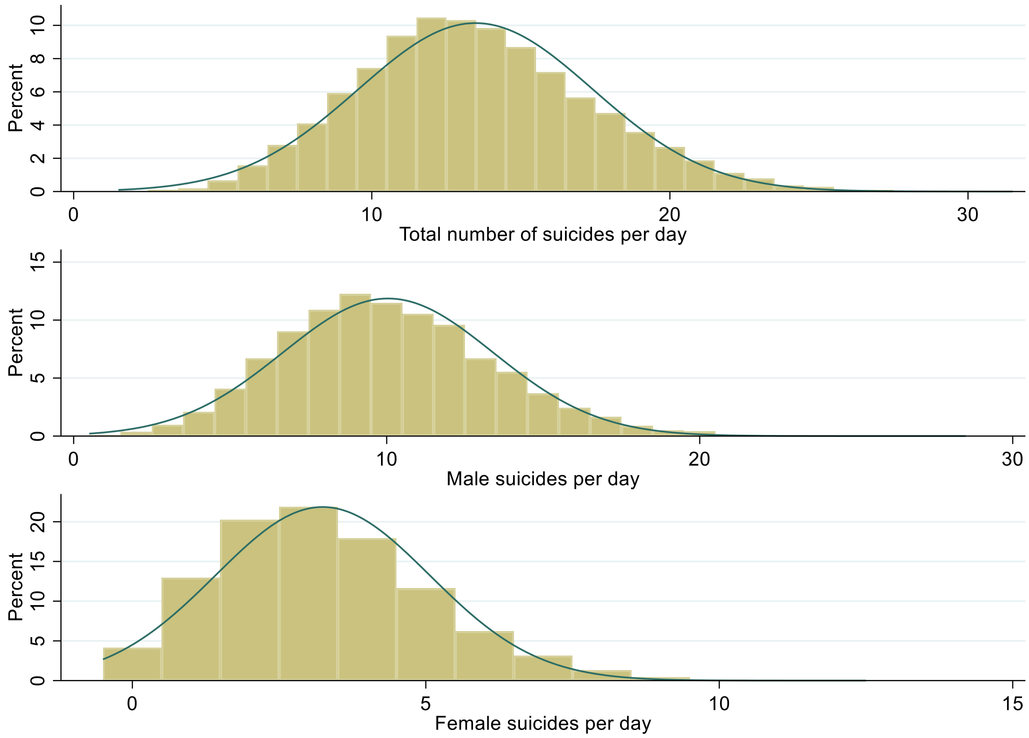
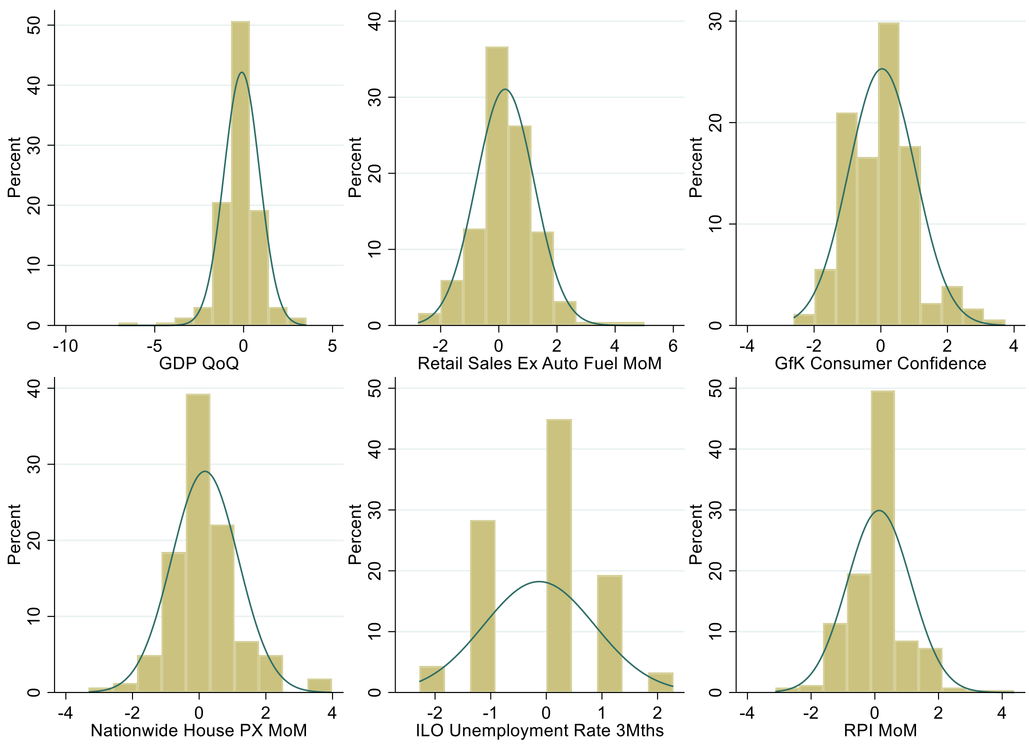
Figure A1. Frequency distribution of daily suicide counts



Notes: The figure depicts the frequency distribution of daily suicide counts in England and Wales for each of three groups: persons (top panel), males (middle panel), and females (bottom panel). The sample period is from January 1, 1997 to December 31, 2017. The solid lines represent the Gaussian distribution.

Figure A2. Frequency distributions of macroeconomic shocks



Notes: The figure depicts the frequency distribution of standardised shocks, or forecast errors, for each of the six UK macroeconomic indicators employed in the analysis. We compute the standardised shocks according to formula (1) in the main body of the paper. The sample period is from January 1, 1997 to December 31, 2017. The solid lines represent the Gaussian distribution.

A.1 Ranking of macroeconomic indicators by amount of media coverage in the UK

To determine which macroeconomic indicators matter the most to the general public in the UK, we assume that public attention and media coverage go hand in hand, and consequently we employ the latter as a proxy for the former. The exact procedure to identify these indicators is described next. First, starting from the universe of all macroeconomic indicators tracked by Bloomberg, we apply a set of filters to ensure that the median forecasts at our disposal are a sufficiently reliable proxy for F, and our estimates of the causal effects of interest are reasonably precise. Namely, we filter out all the indicators for which the mean number of analyst forecasts included in the Bloomberg surveys is less than 10 *or* the number of observations (i.e. shocks) available is less than 100. A total of 27 indicators survive this initial screening. Next, to determine which of these are the most widely covered by the UK news media, we employ *GDELT Summary*, an online news search platform that allows one to search "the textual and visual narratives of the world's news media" using simple keywords (https://blog.gdeltproject.org/announcing-gdelt-summary/). Its database covers the period from the beginning of January 2017 to the present, and we stopped the search at the end of December 2021.

Table A1 below displays the resulting statistics. With an average count of about 87 hits per day, GDP is by far the macroeconomic indicator most commonly mentioned by the UK news media. Retail sales ranks second, followed by consumer confidence, consumer price index (CPI), house prices, and the unemployment rate. Since the top six indicators attract a much greater amount of media attention than the rest, we choose to focus on them in our analysis. There is one exception, CPI. Both CPI and RPI (i.e. the Retail Price Index, which ranks 8^{th} in Table A1) are inflation measures, and they are jointly announced by the ONS. However, in the Bloomberg database from which we obtain the data, CPI forecasts are available from January 2004, while RPI forecasts cover the entire sample period. Thus, to maximise the number of data points in the sample and the precision of our estimates, we decide to use the RPI as our inflation indicator.

Table A1. Ranking of macroeconomic indicators by amount of media coverage in the UK

Rank	Indicator (Bloomberg event)	Search term	Average daily count	Notes
1	GDP QoQ	gdp	86.878	
2	Retail Sales Ex Auto Fuel MoM	retail sales	32.321	
3	GfK Consumer Confidence	consumer confidence	27.565	
4	CPI MoM	cpi	21.958	
5	Nationwide House PX MoM	house price	20.890	
6	ILO Unemployment Rate 3Mths	unemployment rate	20.042	
7	Avg Earnings inc bonus 3M/YoY	average earnings	12.248	Forecast survey discontinued in February 2010
8	RPI MoM	rpi	9.616	
9	Industrial Production MoM	industrial production	8.635	
10	Bank of England Bank Rate	bank rate	6.202	
11	Jobless Claims Change	jobless claims	5.989	Forecast survey discontinued in March 2017
12	Trade Balance GBP/Mn	trade balance	3.926	
13	Mortgage Approvals	mortgage approvals	3.022	
14	Claimant Count Rate	claimant count	2.698	Forecast survey discontinued in March 2017
15	Manufacturing Production MoM	manufacturing production	2.341	
16	Public Sector Net Borrowing	public sector net borrowing	2.217	
17	RICS House Price Balance	house price balance	0.330	
18	CPI Core YoY	cpi core	0.303	
19	PPI Input NSA MoM	ppi input	0.178	
20	PPI Output NSA MoM	ppi output	0.157	
21	Net Consumer Credit	net consumer credit	0.155	
22	Visible Trade Balance GBP/Mn	visible trade balance	0.048	
23	PPI Output Core NSA MoM	ppi output core	0.035	
24	Trade Balance Non EU GBP/Mn	trade balance non eu	0.033	
25	Public Finances (PSNCR)	public sector net cash	0.013	
26	Net Lending Sec. on Dwellings	net lending secured	0.010	
27	RPI Ex Mort Int.Payments (YoY)	rpi excluding	0.004	

Notes: This table ranks the 27 UK macroeconomic indicators that survive our screening criteria by the amount of attention that they received from online news media in the UK. To establish this ranking, we searched *GDELT Summary*, an online news search platform, using the keywords displayed in the third column. The search criteria are as follows: Dataset = Global Online News Coverage; Country = United Kingdom; Language = English; Displays = Raw Article Count; Time Period = from January 1, 2017 to December 31, 2021. (Note that these data are available from the beginning of 2017.) The first column displays the estimated rank of each indicator, the second column displays the name of the indicator (as reported by Bloomberg), the fourth column displays the average number of hits per day that the search returned, and the last column provides information about some of the indicators for which the analyst forecast survey conducted by Bloomberg has been discontinued.

A.2 Hypothesis derivation

As discussed in section 2.3 of the main body of the paper, Hamermesh and Soss's (1974) model predicts that the suicide rate is a decreasing function of permanent income. The implication is that any macroeconomic factor (such as GDP growth, retail sales, consumer confidence, house prices, unemployment rate, and the RPI) that may affect estimated permanent income may also affect the suicide rate.

Specifically, under the assumption that individuals suffer from an extrapolation bias and project the present into the future when forming expectations (Fuster et al., 2010), we conjecture that the average individual interprets an increase in GDP growth as signalling higher future GDP growth, better personal economic prospects (Roth & Wohlfart, 2020) and, thus, higher permanent income. The implication is that positive shocks to GDP growth raise discounted lifetime utility, as follows

$$\frac{\overset{+}{\Delta Z}}{\Delta GDP\ growth} = \frac{\overset{+}{\Delta Z}}{\Delta Y_p} \times \frac{\overset{+}{\Delta Y_p}}{\Delta GDP\ growth} \qquad \textbf{(A1)}$$

Since higher lifetime utility, *Z*, reduces the fraction of the population for which inequality (4) is satisfied, the first testable hypothesis is:

H1a: There exists a negative relation between GDP growth and the suicide rate.

Analogous reasoning applies to shocks to retail sales and consumer confidence. Since both are leading economic indicators (Ferrara et al., 2010; McIntyre, 2007), we conjecture that the average individual interprets an increase in retail sales or consumer confidence as signalling higher future GDP growth, better personal economic prospects, higher future wages, and, thus, higher permanent income. This implies:

$$\frac{\overset{+}{\Delta Z}}{\Delta Retail\ sales} = \frac{\overset{+}{\Delta Z}}{\Delta Y_p} \times \frac{\overset{+}{\Delta Y_p}}{\Delta GDP\ growth} \times \frac{\overset{+}{\Delta GDP\ growth}}{\Delta Retail\ sales} \tag{A2}$$

$$\frac{\overset{+}{\Delta Z}}{\Delta Consumer\ confidence} = \frac{\overset{+}{\Delta Z}}{\Delta Y_p} \times \frac{\overset{+}{\Delta Y_p}}{\Delta GDP\ growth} \times \frac{\overset{+}{\Delta GDP\ growth}}{\Delta Consumer\ confidence} \tag{A3}$$

Formulas (A2) and (A3) lead to the following hypotheses:

H1b: There exists a negative relation between retail sales and the suicide rate.

H1c: There exists a negative relation between consumer confidence and the suicide rate.

As for house prices, we draw on Chahrour & Gaballo's (2020) neoclassical model with housing and learning and conjecture that they play an informational role. Since "[m]ost fluctuations in local house prices are driven by local labour productivity", higher house prices are "misinterpreted by households as good news about future wages" and, thus, "as signalling higher permanent income" (Chahrour & Gaballo, 2020). This implies:

$$\frac{\overset{+}{\Delta Z}}{\Delta House\ prices} = \frac{\overset{+}{\Delta Z}}{\Delta Y_p} \times \frac{\overset{+}{\Delta Y_p}}{\Delta House\ prices} \tag{A4}$$

which leads to the fourth hypothesis:

H1d: There exists a negative relation between house prices and the suicide rate.

For parsimony, we group hypotheses *H1a*, *H1b*, *H1c*, and *H1d*, which are connected by a common thread, into hypothesis *H1*, as follows:

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

Estimated permanent income can also be affected by changes in unemployment. Higher unemployment rates make it more difficult "for employed workers to find alternative jobs, and

[…][make it easier] for firms to find alternative workers" (Blanchard, 1991). Thus, higher rates of unemployment reduce the bargaining power of the employed and unemployed. Therefore, we conjecture that the average individual revises his wage growth expectations downward in response to an increase in the unemployment rate (Campos & Reggio, 2015), which leads to a lower estimated permanent income. This implies:

$$\frac{\overset{-}{\Delta Z}}{\Delta Unemployment\ rate} = \frac{\overset{+}{\Delta Z}}{\Delta Y_p} \times \frac{\overset{-}{\Delta Y_p}}{\Delta Unemployment\ rate} \qquad \textbf{(A5)}$$

Formula (A5) leads to the following hypothesis:

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

Lastly, the impact of RPI on permanent income and the overall suicide rate is ambiguous. On the one hand, a higher inflation rate lowers permanent income in real terms, thus lowering consumption and discounted lifetime utility. On the other hand, state pensions in the UK are uprated against an inflation indicator (RPI until April 2011, and the maximum of CPI, average earnings growth, or 2.5%, thereafter) (Joyce & Levell, 2011). As such, holding constant the inflation experienced by older households (i.e. pensioner inflation), which may be different from that measured by changes in RPI and CPI, an increase in RPI represents an increase in real pension benefits for retired individuals. If pensioners extrapolate these increased benefits into the future, they may revise their estimated permanent incomes upward. In sum, these two different lines of reasoning have conflicting implications, as follows:

$$\frac{\overset{-}{\Delta Z}}{\Delta RPI} = \frac{\overset{+}{\Delta Z}}{\Delta Y_p} \times \frac{\overset{-}{\Delta Y_p}}{\Delta RPI} \quad or \quad \frac{\overset{+}{\Delta Z}}{\Delta RPI} = \frac{\overset{+}{\Delta Z}}{\Delta Y_p} \times \frac{\overset{+}{\Delta Y_p}}{\Delta RPI} \qquad \textbf{(A6)}$$

Therefore, the last hypothesis is

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

A.3 Quality of professional economic forecasts

While analysts have their reputation at stake and, therefore, have an incentive to generate as accurate forecasts as possible, previous studies have shown that some professional economic forecasts may be, to some extent, biased (Batchelor, 2007). For this reason, before estimating equation (5), we find it useful to examine the quality of the sample of professional forecasts at our disposal. We start by running an unbiasedness test, as in Holden and Peel (1990). Forecasts concerning indicator *i* are unbiased if the expected value of the forecast error equals zero, that is

$$E[A_i - F_i] = 0 \tag{A7}$$

which can be tested by estimating the following regression equation separately for each indicator *i*

$$A_t - F_t = \alpha + \varepsilon_t \tag{A8}$$

Unbiasedness requires that the mean forecast error be equal to zero, i.e. $\alpha = 0$. Before estimating equation (A8), we run an augmented Dickey-Fuller test to determine whether all six series are stationary. The results of the stationarity tests, based on Kripfganz and Schneider (2020), are summarised in column 1 of Table A2 below. They reveal that the null hypothesis of a unit root can always be rejected at the 1% confidence level. Column 2 displays the estimated alphas (i.e. $\hat{\alpha}$) based on equation (A8). The corresponding p-values are based on Newey & West's (1987) standard errors with a lag truncation parameter of $T^{1/4}$ (T = number of observations), which are robust to heteroscedasticity and autocorrelation (HAC) in the error term. It emerges that the forecasts concerning GDP growth, consumer confidence, and the unemployment rate are unbiased, as there is no statistical evidence that the average forecast error, α, differs from 0.

Table A2. Unbiasedness and efficiency of macroeconomic forecasts

Indicator	(1) *A-F* ADF Test Reject H_0 at 1%?	(2) $\hat{\alpha}$ H_0: $\alpha = 0$ (p-value)	(3) $\frac{\hat{\alpha}}{\text{std}(A)}$	(4) *A-F* Breusch-Godfrey test χ^2 (p-value)	(5) *A-F* Wald-Wolfowitz Runs test Z (p-value)	(6) Adj. R^2 Current forecast error regressed on past forecast errors
GDP	Yes	-0.00014		10.49	-1.59	
		(0.188)		(0.572)	(0.112)	
Retail sales	Yes	0.00157^{***}	0.174	24.08^{**}	3.79^{***}	0.043
		(0.000)		(0.019)	(0.000)	
Consumer confidence	Yes	0.10497		11.4	1.21	
		(0.544)		(0.494)	(0.227)	
House prices	Yes	0.00106^{*}	0.134	15.42	0.85	
		(0.054)		(0.219)	(0.393)	
Unemployment	Yes	-0.00011		7.29	-1.59	
		(0.109)		(0.837)	(0.112)	
RPI	Yes	0.00022^{**}	0.058	24.21^{**}	1.46	0.057
		(0.033)		(0.019)	(0.144)	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When it comes to retail sales (RPI, house prices), the null hypothesis that $\alpha = 0$ can be rejected at the 1% (5%, 10%) significance level. Specifically, the three estimated alphas are positive, suggesting that analysts' expectations concerning these three indicators tend to be consistently below target. To get a sense for the size of these biases, in column 3 we divide $\hat{\alpha}$ by the standard deviation of A: the results vary between 5.8% and 17.4% of a standard deviation, suggesting that the biases are mild.

To investigate the efficiency of the forecasts, we run a Breusch–Godfrey autocorrelation test (with a maximum of 12 lags) on the residuals from equation (A8), where the null hypothesis is that past forecast errors do not help predict future forecast errors. The results of these tests, displayed in column 4 of Table A2, reveal that for retail sales and RPI we can reject the null hypothesis of no autocorrelation in the forecast errors at conventional significance levels. However, consistent with the interpretation that the forecasts are fairly efficient, the adjusted R^2 (column 6) are quite low: 4.3% for retail sales, and 5.7% for RPI. Put another way, the portion of the variation in the current forecast error explained by past forecast errors is quite small.

Lastly, we conduct a Wald-Wolfowitz runs test for randomness, which is a nonparametric test of the null hypothesis that the sequence of forecast errors, $A_t - F_t$, is generated from a random process. The outcomes are reported in column 5 of Table A2, and what emerges is that only in the case of retail sales does the test reject the null hypothesis of randomness at conventional significance levels.

In summary, 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 this 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.

A.4 Investigating potential near-multicollinearity among macroeconomic surprise indicators

A question that deserves attention is whether the estimates generated by fitting equation (5) and presented in Table 2 of the main body of the paper are unduly influenced by near-multicollinearity among the six macroeconomic surprise indicators under observation. (We thank an anonymous reviewer for raising this point.) To address this question, we start by computing some statistics on the frequency with which multiple announcements concerning these indicators occur on the same day. What emerges is that only about 7% of the announcement days in the sample involve multiple announcements. Specifically, concurrent announcements regarding two indicators occur on 6.19% of the announcement days, and concurrent announcements regarding three indicators occur on 0.95% of the announcement days. No more than three announcements occur on the same day. Put another way, multiple contemporaneous announcements concerning these six macroeconomic indicators occur very rarely in our sample period. Consequently, near-multicollinearity is unlikely to be a problem when estimating equation (5).

As a second approach, we compute the correlation coefficients between pairs of macroeconomic surprise indicators. In Table A3a below, the Pearson's correlation matrix is computed using all days in the sample period, whereas in Table A3b the Pearson's correlation matrix is computed using only days with at least one macroeconomic surprise.

Table A3a. Pearson's correlation matrix for the group of macroeconomic surprise indicators (all days in the sample period)

	GDP	Retail sales	Consumer confidence	House prices	Unemployment rate	RPI
GDP	1					
Retail sales	-0.0333	1				
Consumer confidence	0.0182	0.00263	1			
House prices	-0.0240	-0.000974	-0.000864	1		
Unemployment rate	-0.000338	0.000770	0.000120	0.000502	1	
RPI	0.000406	-0.000926	-0.000144	-0.000603	0.000477	1

Table A3b. Pearson's correlation matrix for the group of macroeconomic surprise indicators (only days with at least one macroeconomic surprise)

	GDP	Retail sales	Consumer confidence	House prices	Unemployment rate	RPI
GDP	1					
Retail sales	-0.0297	1				
Consumer confidence	0.0188	0.00133	1			
House prices	-0.0216	-0.00646	-0.00172	1		
Unemployment rate	-0.00223	0.00511	0.000793	0.00332	1	
RPI	0.00269	-0.00614	-0.000954	-0.00399	0.00315	1

It is clear that all correlation coefficients are very low. The value of the highest correlation coefficient is about 3%, indicating that the variables in question are far from highly correlated, and consequently near-multicollinearity does not represent a problem in equation (5).

As a third approach, we estimate the variance inflation factors (VIF) for the six macroeconomic surprise indicators that appear in equation (5), and we find that they range between 1.01 and 1.02. These values are much lower than the “rule-of-thumb” threshold of 10 that the literature typically indicates as cause for concern (O’Brien, 2007), which leads us to conclude that our estimates are not affected by near-multicollinearity.

As a fourth and last approach, we re-estimate equation (5) but include in the regression only one macroeconomic surprise indicator at a time. Table A4 below displays the resulting estimates. The results are nearly identical to those presented in column 6 of Table 2, which indicates that near-multicollinearity does not represent a problem in equation (5).

Table A4. Robustness test: one macroeconomic surprise indicator at a time

		Dependent variable: Daily suicide rate per 100,000 people					
	Hypothesis	(1)	(2)	(3)	(4)	(5)	(6)
GDP	-	-0.000559					
		(-1.18)					
Retail sales	-		-0.000687^{*}				
			(-1.83)				
Consumer confidence	-			-0.00116^{**}			
				(-2.14)			
House prices	-				-0.00121^{***}		
					(-2.87)		
Unemployment rate	+					0.000291	
						(0.59)	
RPI	+/-						-0.000707
							(-1.61)
Linear time trend		Yes	Yes	Yes	Yes	Yes	Yes
Seasonalities		Yes	Yes	Yes	Yes	Yes	Yes
ln(EPU) & ln(GPR)		Yes	Yes	Yes	Yes	Yes	Yes
Misery		Yes	Yes	Yes	Yes	Yes	Yes
Financial market returns		Yes	Yes	Yes	Yes	Yes	Yes
ln(FTSE_VIX)		Yes	Yes	Yes	Yes	Yes	Yes
Lags of dep. variable		Yes	Yes	Yes	Yes	Yes	Yes
N		6572	6572	6572	6572	6572	6572
Adj. R^2		0.079	0.079	0.080	0.080	0.079	0.079

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

A.5 Alternative time trends and dependent variable

We run a number of sensitivity tests to investigate whether the results presented in Section 3.1 of the main body of the paper are robust. The first battery of tests involves the time trend, which in Table 2 is assumed to be linear. Imposing alternative time trends (quadratic, cubic, logarithmic, hyperbolic) has no material impact on the main results (see columns 1-4 of Table A5 below). Analogously, using year dummy variables in place of a time trend (column 5 of Table A5) 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) (column 6 of Table A5) leaves the results qualitatively unchanged.

Table A5. Alternative time trends and dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Daily suicide rate	Daily suicide rate	Daily suicide rate	Daily suicide rate	Daily suicide rate	Abnormal daily suicide rate
GDP	-0.000652	-0.000630	-0.000605	-0.000609	-0.000581	-0.000641
	(-1.37)	(-1.32)	(-1.26)	(-1.27)	(-1.22)	(-1.36)
Retail sales	-0.000714*	-0.000696*	-0.000715*	-0.000713*	-0.000772**	-0.000728*
	(-1.88)	(-1.83)	(-1.88)	(-1.88)	(-2.07)	(-1.87)
Consumer confidence	-0.00113**	-0.00113**	-0.00114**	-0.00114**	-0.00111**	-0.00113**
	(-2.09)	(-2.08)	(-2.11)	(-2.10)	(-2.03)	(-2.07)
House prices	-0.00117***	-0.00117***	-0.00123***	-0.00122***	-0.00108**	-0.00118***
	(-2.82)	(-2.83)	(-2.99)	(-2.98)	(-2.53)	(-2.81)
Unemployment rate	0.000321	0.000340	0.000295	0.000294	0.000421	0.000350
	(0.65)	(0.69)	(0.60)	(0.60)	(0.85)	(0.70)
RPI	-0.000676	-0.000673	-0.000714	-0.000711	-0.000560	-0.000630
	(-1.54)	(-1.53)	(-1.63)	(-1.62)	(-1.27)	(-1.42)
Linear + quadratic trend	Yes	Yes	No	No	No	No
Cubic trend	No	Yes	No	No	No	No
Logarithmic trend	No	No	Yes	No	No	No
Hyperbolic trend	No	No	No	Yes	No	No
Year dummies	No	No	No	No	Yes	No
Seasonalities	Yes	Yes	Yes	Yes	Yes	Yes
ln(EPU) & ln(GPR)	Yes	Yes	Yes	Yes	Yes	Yes
Misery	Yes	Yes	Yes	Yes	Yes	Yes
Financial market returns	Yes	Yes	Yes	Yes	Yes	Yes
ln(FTSE_VIX)	Yes	Yes	Yes	Yes	Yes	Yes
Lags of dep. variable	Yes	Yes	Yes	Yes	Yes	No
N	6572	6572	6572	6572	6572	6572
Adj. R^2	0.083	0.084	0.081	0.081	0.092	0.065

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

A.6 Alternative model specifications

In a second series of tests, we employ alternative methodologies to model suicidal behaviour. Namely, instead of modelling the daily suicide rate per 100,000 persons, we model the daily suicide count, *Suicides*. The first alternative specification is a log-linear model, as follows:

$$ln(Suicides_t) = \alpha + \boldsymbol{z}_t'\boldsymbol{\beta} + \varphi_1 ln(Suicides_{t-1}) + \omega_1 ln(Population_t) + \varepsilon_t \quad \textbf{(A9)}$$

where $\boldsymbol{z}$ is the vector of explanatory variables that appear in column 6 of Table 2, with the exclusion of the lagged suicide rate, and $Population_t$ is the (linearly interpolated) population in England and Wales on day *t*. The one-day lagged suicide count appears on the right-hand side of the equation.

The OLS estimates, displayed in column 1 of Table A6 below, are consistent with those in Table 2. Based on Newey-West (HAC) robust standard errors, the coefficients on retail sales, consumer confidence, and house prices are statistically significant at conventional levels, and their signs are as expected. For example, a negative one-standard-deviation surprise in house prices increases the daily number of suicides by 4.5% (=exp(0.0470)), while a negative one-standard deviation surprise in consumer confidence raises the suicide count by 4.2% (=exp(0.0411)).

The second alternative specification is a static Poisson count model, which assumes that $Suicides_t$ ~ Poisson(μ_t) and

$$\ln(\mu_t) = \alpha + \boldsymbol{z}_t'\boldsymbol{\beta} + ln(Population_t) \quad \textbf{(A10)}$$

where *Population*, as defined above, is the exposure. We compute HAC robust standard errors based on Newey-West weights. The maximum likelihood estimates are displayed in column 2 of Table A6, revealing that they are very similar to those generated by model (A9).

Table A6. Alternative model specifications

	Log-linear	Static Poisson	Static negative binomial	Dynamic Poisson		Brännäs INAR(3)
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ln(Number of suicides)	Number of suicides	Number of suicides	Number of suicides	Number of suicides	Number of suicides
GDP	-0.0333	-0.0244	-0.0245	-0.0237	-0.0240	-0.0234
	(-1.57)	(-1.31)	(-1.30)	(-1.28)	(-1.29)	(-1.22)
Retail sales	-0.0299*	-0.0310*	-0.0311*	-0.0312*	-0.0315*	-0.0334*
	(-1.76)	(-1.89)	(-1.89)	(-1.91)	(-1.93)	(-1.84)
Consumer confidence	-0.0411*	-0.0477**	-0.0475**	-0.0479**	-0.0480**	-0.0574**
	(-1.84)	(-2.03)	(-2.03)	(-2.05)	(-2.06)	(-2.13)
House prices	-0.0470**	-0.0512***	-0.0512***	-0.0514***	-0.0515***	-0.0579***
	(-2.44)	(-2.87)	(-2.87)	(-2.92)	(-2.94)	(-2.86)
Unemployment rate	0.00763	0.0108	0.0108	0.0120	0.0119	0.0139
	(0.37)	(0.54)	(0.54)	(0.60)	(0.59)	(0.61)
RPI	-0.0233	-0.0289	-0.0288	-0.0289	-0.0285	-0.0333
	(-1.31)	(-1.59)	(-1.59)	(-1.58)	(-1.56)	(-1.61)
ln(Population)	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
Seasonalities	Yes	Yes	Yes	Yes	Yes	No
ln(EPU) & ln(GPR)	Yes	Yes	Yes	Yes	Yes	Yes
Misery	Yes	Yes	Yes	Yes	Yes	Yes
Financial market returns	Yes	Yes	Yes	Yes	Yes	Yes
ln(FTSE_VIX)	Yes	Yes	Yes	Yes	Yes	Yes
Lags of ln(number of suicides)	Yes	No	No	No	Yes	No
Lags of number of suicides	No	No	No	No	No	Yes
N	6572	6572	6572	6569	6572	6572
LB		43.408	43.447	13.792	13.744	13.751
Rho^2		0.074	0.074	0.077	0.077	0.077

Notes: *t* statistics in parentheses in columns 1 and 6. *z* statistics in parentheses in columns 2-5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Since the Poisson model is based on the restrictive assumption of equidispersion, we also estimate a static negative binomial mean-dispersion model where the right-hand side of equation (A10) is assumed to contain an extra variable ν_t, such that e^{ν_t} ~ Gamma$(1/\alpha, \alpha)$, α being the overdispersion parameter. The estimates are shown in column 3 of Table A6, and they are almost identical to those in column 2.

Though static Poisson and negative binomial models are geared toward static count data, Cameron and Trivedi (2013) claim that the use of HAC robust standard errors produces valid statistical inference even in the presence of serial correlation in the dependent variable. Nevertheless, since we are modelling a time series of suicide counts, to ensure the robustness of our findings we also employ three dynamic count-data models popularised by Cameron and Trivedi (2013). The first model is based on Davis et al.'s (2003) work:

$$\ln(\mu_t) = \alpha + \boldsymbol{z}_t'\boldsymbol{\beta} + ln(Population_t) + \sum_{j=1}^{J} \gamma_j Z_{t-j} \quad \textbf{(A11)}$$

where Z is the Pearson residual. In simple terms, in this specification we add residual-like terms to the right-hand side until the Ljung-Box test no longer rejects the null hypothesis of no autocorrelation in the Pearson residuals.

The second dynamic model is based on Zeger and Qaqish's (1988) work:

$$\ln(\mu_t) = \alpha + \boldsymbol{z}_t'\boldsymbol{\beta} + ln(Population_t) + \sum_{k=1}^{K} \varphi_k ln(Suicides_{t-k}) \quad \textbf{(A12)}$$

In this case, we add log-transformed lags of *Suicides* to the right-hand side until the Ljung-Box test no longer rejects the null hypothesis of no autocorrelation in the Pearson residuals.

The third dynamic model is based on Brännäs (1995) INAR model:

$$\mu_t = \sum_{k=1}^{K} \varphi_k Suicides_{t-k} + exp(\alpha + \boldsymbol{z}_t'\boldsymbol{\beta} + ln(Population_t)) \quad \textbf{(A13)}$$

Here we estimate the parameters by NLS, and we add lags of *Suicides* to the right-hand side until the Ljung-Box test no longer rejects the null hypothesis of no autocorrelation in the Pearson residuals.

The estimates generated by fitting equations (A11), (A12), and (A13) are displayed in columns 4-6 of Table A6, respectively. They are consistent with one another and qualitatively very similar to those obtained from the static count-data models, which leads us to conclude that our results are robust to alternative model specifications. Based on Rho^2 (i.e. the squared correlation coefficient between actual and predicted numbers of suicides), model (A12) achieves the best goodness of fit among the five count-data models. However, the improvement compared to the static count-data models is marginal.

A.7 Lagged effects

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 first re-estimate equation (5) with lags of the individual macroeconomic surprise indicators. Specifically, we include between one and four lags of S_i. The estimates are reported in Table A7 below, where the number of lags included in the regression increases moving from column 1 to 4. The vast majority of the coefficients of interest are not statistically different from zero. Given the large number of coefficients tested, it is not surprising that 2 out of 60 (=3.33%) are statistically significant at least at the 10% level. This frequency is in line with what one would expect to observe by pure chance.

However, since individual lags of a predictor might be highly correlated, we also test all lags at once: Namely, we test the null hypothesis that the *sum* of the four lagged effects of each predictor is equal to zero. Untabulated results show that we can never reject this null hypothesis. This leads us to conclude that there is no evidence that individual shocks to the six macroeconomic indicators in our sample have a lagged impact on suicidal behaviour.

Yet, it is also possible that suicidal behaviour is affected by cumulative macroeconomic shocks that occur over a period of several months. For example, during an economic recession multiple negative shocks may happen one after another, and such accumulated shocks may have a more detectible effect than individual shocks. (We thank an anonymous reviewer for raising this point.) To investigate this question, we re-estimate equation (5) with the inclusion of cumulative shocks to the six macroeconomic indicators in our sample. The results are displayed in Table A8 below.

Table A7. Lagged impact of macroeconomic shocks

	Dependent variable: Daily suicide rate per 100,000 people			
	(1)	(2)	(3)	(4)
GDP(t-1)	-0.000121	-0.000117	-0.000123	-0.000150
	(-0.28)	(-0.27)	(-0.28)	(-0.34)
GDP(t-2)		0.000183	0.000192	0.000199
		(0.39)	(0.41)	(0.43)
GDP(t-3)			-0.000563	-0.000563
			(-1.14)	(-1.14)
GDP(t-4)				0.000322
				(0.67)
Retail sales(t-1)	0.000298	0.000294	0.000328	0.000295
	(0.77)	(0.77)	(0.83)	(0.75)
Retail sales(t-2)		0.000421	0.000421	0.000295
		(0.92)	(0.92)	(0.67)
Retail sales(t-3)			0.000618	0.000627
			(1.37)	(1.39)
Retail sales(t-4)				0.000141
				(0.30)
Consumer confidence(t-1)	0.000280	0.000272	0.000273	0.000235
	(0.58)	(0.56)	(0.56)	(0.49)
Consumer confidence(t-2)		-0.0000224	-0.0000388	-0.0000439
		(-0.06)	(-0.10)	(-0.11)
Consumer confidence(t-3)			0.000304	0.000302
			(0.56)	(0.56)
Consumer confidence(t-4)				-0.000356
				(-0.73)
House prices(t-1)	-0.000745	-0.000744	-0.000757	-0.000749
	(-1.38)	(-1.38)	(-1.40)	(-1.39)
House prices(t-2)		-0.000133	-0.000134	-0.000126
		(-0.26)	(-0.26)	(-0.25)
House prices(t-3)			-0.000460	-0.000460
			(-0.83)	(-0.83)
House prices(t-4)				0.0000430
				(0.11)
Unemployment rate(t-1)	-0.000295	-0.000246	-0.000246	-0.000245
	(-0.59)	(-0.49)	(-0.49)	(-0.49)
Unemployment rate(t-2)		-0.000282	-0.000261	-0.000259
		(-0.63)	(-0.58)	(-0.57)
Unemployment rate(t-3)			-0.000316	-0.000402
			(-0.65)	(-0.82)
Unemployment rate(t-4)				0.000735*
				(1.77)
RPI(t-1)	0.000377	0.000380	0.000382	0.000378
	(0.91)	(0.91)	(0.92)	(0.91)
RPI(t-2)		0.000639	0.000642	0.000637
		(1.43)	(1.44)	(1.43)
RPI(t-3)			0.000289	0.000281
			(0.69)	(0.67)
RPI(t-4)				-0.00114**
				(-2.47)

Linear time trend	Yes	Yes	Yes	Yes
Seasonalities	Yes	Yes	Yes	Yes
ln(EPU) & ln(GPR)	Yes	Yes	Yes	Yes
Misery	Yes	Yes	Yes	Yes
Financial market returns	Yes	Yes	Yes	Yes
ln(FTSE_VIX)	Yes	Yes	Yes	Yes
Lags of dep. variable	Yes	Yes	Yes	Yes
N	6572	6572	6572	6572
Adj. R^2	0.079	0.078	0.078	0.079

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

Table A8. Effects of contemporaneous vs. cumulative macroeconomic shocks

	Dependent variable: Daily suicide rate per 100,000 people			
	(1)	(2)	(3)	(4)
GDP	-0.000633	-0.000655	-0.000663	-0.000661
	(-1.34)	(-1.40)	(-1.40)	(-1.39)
Retail sales	-0.000758**	-0.000774**	-0.000770**	-0.000772**
	(-2.02)	(-2.07)	(-2.06)	(-2.06)
Consumer confidence	-0.00112**	-0.00114**	-0.00115**	-0.00115**
	(-2.07)	(-2.09)	(-2.11)	(-2.10)
House prices	-0.00117***	-0.00116***	-0.00116***	-0.00114***
	(-2.79)	(-2.77)	(-2.79)	(-2.71)
Unemployment rate	0.000286	0.000295	0.000285	0.000283
	(0.57)	(0.59)	(0.57)	(0.57)
RPI	-0.000686	-0.000682	-0.000686	-0.000668
	(-1.57)	(-1.56)	(-1.56)	(-1.53)
Cumulative_GDP	0.0000206	0.0000274	0.00000915	0.00000715
	(0.37)	(0.55)	(0.22)	(0.19)
Cumulative_retail sales	-0.0000643	-0.0000299	-0.00000297	0.0000162
	(-1.01)	(-0.55)	(-0.06)	(0.36)
Cumulative_consumer confidence	-0.00000147	-0.0000193	-0.0000395	-0.0000739
	(-0.02)	(-0.33)	(-0.71)	(-1.44)
Cumulative_house prices	-0.000173***	-0.000160***	-0.000139***	-0.0000933**
	(-2.59)	(-2.80)	(-2.76)	(-2.07)
Cumulative_unemployment rate	-0.0000355	-0.0000269	-0.0000119	-0.0000674
	(-0.59)	(-0.51)	(-0.25)	(-1.55)
Cumulative_RPI	-0.0000695	-0.0000511	-0.0000398	-0.0000392
	(-1.15)	(-1.00)	(-0.88)	(-0.92)
Linear time trend	Yes	Yes	Yes	Yes
Seasonalities	Yes	Yes	Yes	Yes
ln(EPU) & ln(GPR)	Yes	Yes	Yes	Yes
Misery	Yes	Yes	Yes	Yes
Financial market returns	Yes	Yes	Yes	Yes
ln(FTSE_VIX)	Yes	Yes	Yes	Yes
Lags of dep. variable	Yes	Yes	Yes	Yes
N	6572	6572	6572	6572
Adj. R^2	0.082	0.083	0.083	0.083

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

In column 1 (2, 3, 4), the variable *Cumulative_GDP* measures the arithmetic sum of the standardised surprises in GDP growth that occurred during the 3 (4, 5, 6) months prior to day *t*. A similar interpretation applies to the other five variables measuring cumulative shocks to the remaining five macroeconomic indicators. What emerges from table A8 is that adding the cumulative shocks to the regression does not alter the estimates of the effects of the contemporaneous macroeconomic shocks. Secondly, only in the case of house prices is there statistical evidence that the suicide rate on day *t* is affected by the cumulative shocks that happened during the recent past. Namely, consistent with hypothesis *H1*, repeatedly lower-than-expected house prices during the previous 3 to 6 months (i.e. cumulative negative surprises) tend to raise the suicide rate on day *t*.

A.8 Analysis by state of public trust in the British government

The way individuals react to a macroeconomic shock may depend on their perceptions about whether and to what extent the government will intervene in response to the shock. For example, a sudden decrease in GDP growth may be viewed with a healthy dose of indifference if individuals believe that the government will step in and introduce appropriate economic policies to boost growth. On the other hand, if individuals have little trust in the government's ability (or willingness) to steer the economy, they are more likely to view a negative shock to GDP growth with despair. A similar logic applies to the other five macroeconomic indicators in our sample. Consequently, the way suicidal behaviour responds to macroeconomic shocks may vary with the level of public trust in government. (We thank an anonymous reviewer for raising this point.)

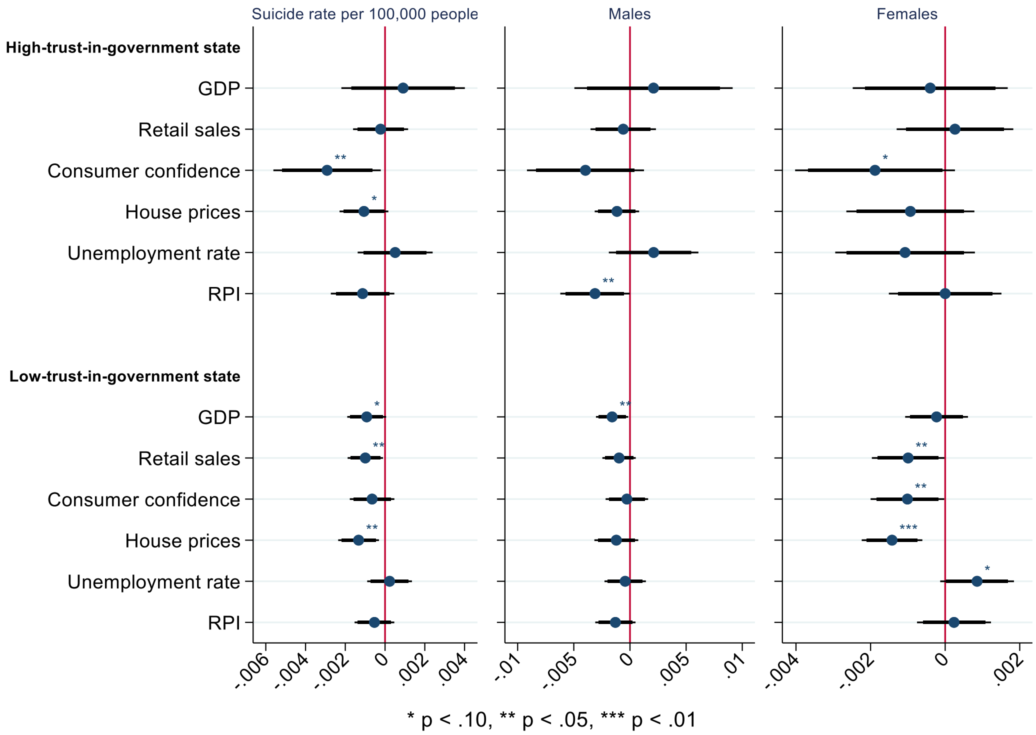
To investigate this matter, we employ data from the British Social Attitudes survey, which has been running every year since 1983 and is based on a representative sample of the British population (https://natcen.ac.uk/BSA). Specifically, one of the questions in the survey is about the level of trust in government; it reads:

> "*How much do you trust British governments of any party to place the needs of the nation above the interests of their own political party?*"

The possible answers are "Just about always/Most of the time", "Only some of the time", and "Almost never". The survey results that we obtain from Curtice et al. (2020) show that there is considerable over-time variability in the level of trust in government, as the share of individuals answering "Almost never" varies between a minimum of 17% in 1998 and a maximum of 40% in 2009. (Note that our sample period is from 1997 to 2017.)

We construct a dummy variable, *Low-trust_in_government*, that takes the value of 1 when the percentage of individuals answering "Almost never" is greater than its sample median, and 0 otherwise. (Note that this question was not asked in 1999, 2004, 2008, 2014, and 2015, and consequently we linearly interpolate to fill in the missing data.) We then re-estimate equation (5) after adding to the right-hand side *Low-trust_in_government* and interactions between *Low-trust_in_government* and each macroeconomic surprise indicator, S_i.

Figure A3. Time-varying responses based on the state of public trust in the British government



The left chart in Figure A3 above displays the point estimates and 95% and 90% confidence intervals of the coefficients on S_i by state of public trust in the British government. 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.) The patterns that emerge are similar to the ones that appear in Figure 2 in the main body of the paper, which displays how the response of the suicide rate varies between states of the economy. At the population level, consistent with hypothesis *H1*, negative house price shocks raise the daily suicide rate regardless of the level of trust in government. There is evidence that negative shocks to GDP growth and retail sales raise the suicide rate, but only when trust in government is low. (Note that our estimates of the effects of retail sales should be treated with caution because, as shown later in Section A.9, they are not robust to debiasing the forecast errors.) And negative shocks to consumer confidence raise the suicide rate, but only in the high-trust regime do we find statistical evidence of this effect.

Breaking down the results further by sex, we find evidence that, among males, negative shocks to GDP growth raise the suicide rate in the low-trust regime and negative shocks to the RPI raise the suicide rate in the high-trust regime. These results are consistent with *H1* and *H3*, respectively. Among females, we find evidence that lower consumer confidence raises the suicide rate regardless of the level of trust in government (*H1*), whereas higher unemployment rates (*H2*), lower house prices (*H1*), and lower retail sales increase the suicide rate in the low-trust regime. (Note the previous caveat about the effect of retail sales.)

In summary, Figure A3 provides empirical evidence that suicidal behaviour responds differently to macroeconomic shocks depending on the level of public trust in government.

A.9 Debiased forecast errors

In Section A.3 of this online Appendix, where we discuss the quality of the professional economic forecasts in our sample, we provide evidence that, in the case of retail sales, house prices, and RPI, analyst forecasts are not fully unbiased and efficient. Therefore, one may worry that the shocks that we quantify with respect to these three indicators are not as good as random, and consequently they cannot be interpreted as exogenous.

To investigate the robustness of our findings, in this section we describe an alternative approach to measuring shocks to these three indicators. Specifically, we assume that, as a result of repeated exposure, the public realises that professional forecasts concerning these three indicators are partly biased and inefficient. In turn, individuals do not take these forecasts at face value, but rather debias them in the process of forming their own expectations. Namely, we assume that individuals use analyst forecasts as an input and calibrate their own expectations according to the following model:

$$A_t - F_t = \alpha + \sum_{k=1}^{N} \beta_k (A_{t-k} - F_{t-k}) + \mu_t \qquad \textbf{(A14)}$$

If $\alpha \neq 0$, as is the case for retail sales, house prices, and RPI (see Section A.3 and Table A2), then the expected analyst forecast error is equal to α, and the public can debias their expectations accordingly. If $\beta_k \neq 0$, then past analyst forecast errors can be used to predict future analyst forecast errors, and the public can adjust their expectations accordingly. Following this line of reasoning, we conjecture that, when the actual value of retail sales (or house prices, or the RPI) is announced on day t, what actually surprises the public (i.e. the random shock) is not analysts' forecast error itself, i.e. $A_t - F_t$, but rather the residual from equation (A14), μ_t. This represents the portion of the change to a macroeconomic indicator that was not predictable in advance by the public.

We estimate equation (A14) separately for each of the three indicators, adding an increasing number of lags (k = 0, 1, 2,…, N) until the residual passes both the Breusch-Godfrey autocorrelation test and the Wald-Wolfowitz runs test for randomness. As shown in columns 1-3 of Table A9 below, the number of lags of the forecast error that is necessary to accomplish this is 3 for the RPI, 1 for retail sales, and 0 for house prices.

Table A9. Debiased forecast errors for retail sales, house prices, and RPI

Indicator	(1) $\hat{\mu}$ Debiased forecast error	(2) $\hat{\mu}$ Breusch-Godfrey test χ^2 (p-value)	(3) $\hat{\mu}$ Wald-Wolfowitz Runs test Z (p-value)
Retail sales	$A_t - F_t = \alpha + \beta(A_{t-1} - F_{t-1}) + \mu_t$	13.5 (0.333)	0.9 (0.366)
House prices	$A_t - F_t = \alpha + \mu_t$		
RPI	$A_t - F_t = \alpha + \sum_{k=1}^{3} \beta_k(A_{t-k} - F_{t-k}) + \mu_t$	18.37 (0.104)	0.46 (0.646)

Notes: Column 1 of this table displays the functional form of the regression equation that we use to estimate the debiased forecast errors for each of three macroeconomic indicators: retails sales, house prices, and the RPI. Each equation is based on equation (A14), and what varies is only the number of lags of the forecast error, A - F, included in the equation. Column 2 displays the χ^2 statistic and p-value from a Breusch-Godfrey test on the residual, μ_t. Column 3 displays the Z statistic and p-value from a Wald-Wolfowitz runs test on the residual, μ_t.

We then re-estimate equation (5), but with a key modification: To quantify the shocks to GDP growth, consumer confidence, and the unemployment rate, we use formula (1), as in Sections 3.1 and 3.2 of the main body of the paper. Instead, we measure a shock to retail sales (or house prices, or the RPI) on day t as $S_t = \widehat{\mu_t} \ / \ Std(\hat{\mu})$, where $\widehat{\mu_t}$ is the estimated debiased forecast error, i.e. the estimated residual from equation (A14), and $Std(\hat{\mu})$ is its sample standard deviation.

The resulting estimates are reported in Table A10 below. What emerges is that our results are largely robust to the way we measure macroeconomic shocks. The only detectible difference concerns the impact of shocks to retail sales: Once we debias analysts' forecasts as explained above, the effect of shocks to retails sales is no longer statistically different from zero at conventional levels. For this reason, our estimates of the effects of shocks to retail sales should be interpreted with caution.

Table A10. Baseline specification: Debiased forecast errors for retail sales, house prices, and RPI

		Dependent variable: Daily suicide rate per 100,000 people					
	Hypothesis	(1)	(2)	(3)	(4)	(5)	(6)
GDP	-	-0.000680	-0.000612	-0.000590	-0.000570	-0.000580	-0.000587
		(-1.40)	(-1.31)	(-1.27)	(-1.22)	(-1.22)	(-1.23)
Retail sales	-	-0.000820**	-0.000657*	-0.000651*	-0.000619	-0.000526	-0.000517
		(-2.00)	(-1.67)	(-1.66)	(-1.57)	(-1.32)	(-1.29)
Consumer confidence	-	-0.00113**	-0.00112**	-0.00115**	-0.00116**	-0.00113**	-0.00115**
		(-2.08)	(-2.07)	(-2.14)	(-2.15)	(-2.08)	(-2.12)
House prices	-	-0.00118***	-0.00123***	-0.00121***	-0.00122***	-0.00120***	-0.00122***
		(-2.58)	(-2.79)	(-2.81)	(-2.85)	(-2.77)	(-2.82)
Unemployment rate	+	0.000362	0.000174	0.000237	0.000240	0.000267	0.000294
		(0.71)	(0.35)	(0.48)	(0.49)	(0.54)	(0.60)
RPI	+/-	-0.000526	-0.000569	-0.000557	-0.000540	-0.000623	-0.000612
		(-1.20)	(-1.33)	(-1.30)	(-1.27)	(-1.40)	(-1.38)
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		0.001	0.095	0.104	0.104	0.080	0.080

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

In Section 3.2. of the main body of the paper, we analyse the effects of macroeconomic shocks on suicidal behaviour after breaking down the data by sex and state of the economy. Due to our concerns about the quality of analyst forecasts regarding retail sales, house prices, and the RPI, we also repeat the same analyses after debiasing the corresponding forecasts as explained above.

The resulting estimates for the male (female) population are reported in Table A11 (Table A12) below, revealing that they are fully in line with those displayed in Table 3 (Table 4) of the main body of the paper. The time-varying responses based on the state of the economy are displayed in Figure A4 below. What emerges is that, with the exception of the effects of shocks to retail sales, all our main results are robust to the way we measure macroeconomic shocks.

In Section A.8 of this online appendix, we analyse the effects of macroeconomic shocks on suicidal behaviour after breaking down the data by state of public trust in the British government. Due to our concerns about the quality of analyst forecasts regarding retail sales, house prices, and the RPI, we also repeat the same analysis after debiasing the corresponding forecasts as explained above. The time-varying responses based on the state of public trust in government are displayed in Figure A5 below. What emerges is that, with the exception of the effects of shocks to retail sales, our main results are largely robust to the way we measure macroeconomic shocks.

Table A11. Male suicide rate: Debiased forecast errors for retail sales, house prices, and RPI

		Dependent variable: Daily suicide rate per 100,000 males					
	Hypothesis	(1)	(2)	(3)	(4)	(5)	(6)
GDP	-	-0.00120	-0.00108	-0.00107	-0.000983	-0.00101	-0.000989
		(-1.46)	(-1.31)	(-1.29)	(-1.17)	(-1.21)	(-1.18)
Retail sales	-	-0.000790	-0.000706	-0.000663	-0.000574	-0.000536	-0.000504
		(-1.08)	(-0.99)	(-0.93)	(-0.80)	(-0.75)	(-0.70)
Consumer confidence	-	-0.000892	-0.00102	-0.00102	-0.00106	-0.00104	-0.00107
		(-0.92)	(-1.06)	(-1.07)	(-1.11)	(-1.08)	(-1.11)
House prices	-	-0.00111	-0.00111	-0.00111	-0.00112	-0.00111	-0.00114
		(-1.33)	(-1.38)	(-1.38)	(-1.39)	(-1.37)	(-1.41)
Unemployment rate	+	0.000145	0.000137	0.000141	0.000146	0.000149	0.000184
		(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.21)
RPI	+/-	-0.00155*	-0.00172**	-0.00176**	-0.00171**	-0.00170**	-0.00165**
		(-1.86)	(-2.12)	(-2.17)	(-2.11)	(-2.08)	(-2.03)
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		0.000	0.050	0.051	0.051	0.052	0.053

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

Table A12. Female suicide rate: Debiased forecast errors for retail sales, house prices, and RPI

	Hypothesis	Dependent variable: Daily suicide rate per 100,000 females					
		(1)	(2)	(3)	(4)	(5)	(6)
GDP	-	-0.000172	-0.000173	-0.000174	-0.000205	-0.000222	-0.000231
		(-0.42)	(-0.43)	(-0.45)	(-0.52)	(-0.56)	(-0.58)
Retail sales	-	-0.000618	-0.000546	-0.000548	-0.000570	-0.000545	-0.000548
		(-1.44)	(-1.29)	(-1.30)	(-1.35)	(-1.29)	(-1.29)
Consumer confidence	-	-0.00132***	-0.00123***	-0.00123***	-0.00123***	-0.00122***	-0.00122***
		(-2.83)	(-2.67)	(-2.69)	(-2.67)	(-2.64)	(-2.65)
House prices	-	-0.00124***	-0.00125***	-0.00129***	-0.00130***	-0.00129***	-0.00129***
		(-3.13)	(-3.12)	(-3.22)	(-3.24)	(-3.24)	(-3.24)
Unemployment rate	+	0.000418	0.000355	0.000377	0.000385	0.000387	0.000390
		(0.93)	(0.79)	(0.83)	(0.85)	(0.85)	(0.86)
RPI	+/-	0.000197	0.000214	0.000221	0.000207	0.000216	0.000213
		(0.47)	(0.52)	(0.53)	(0.49)	(0.51)	(0.51)
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A4. Time-varying responses based on the state of the economy: Debiased forecast errors for retail sales, house prices, and RPI

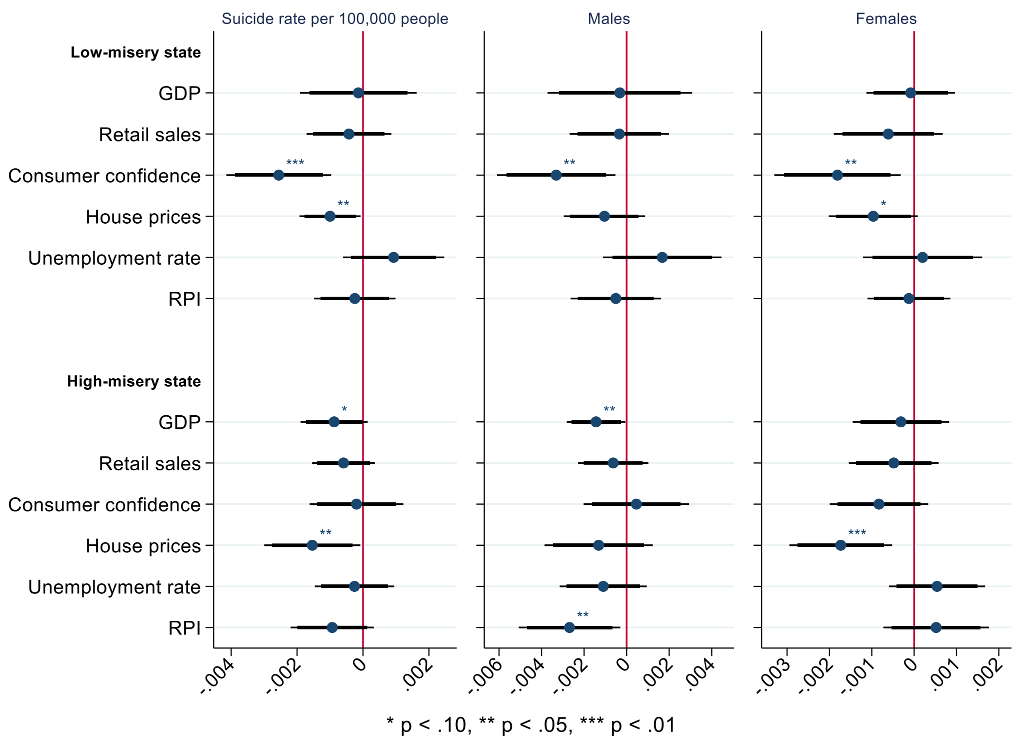
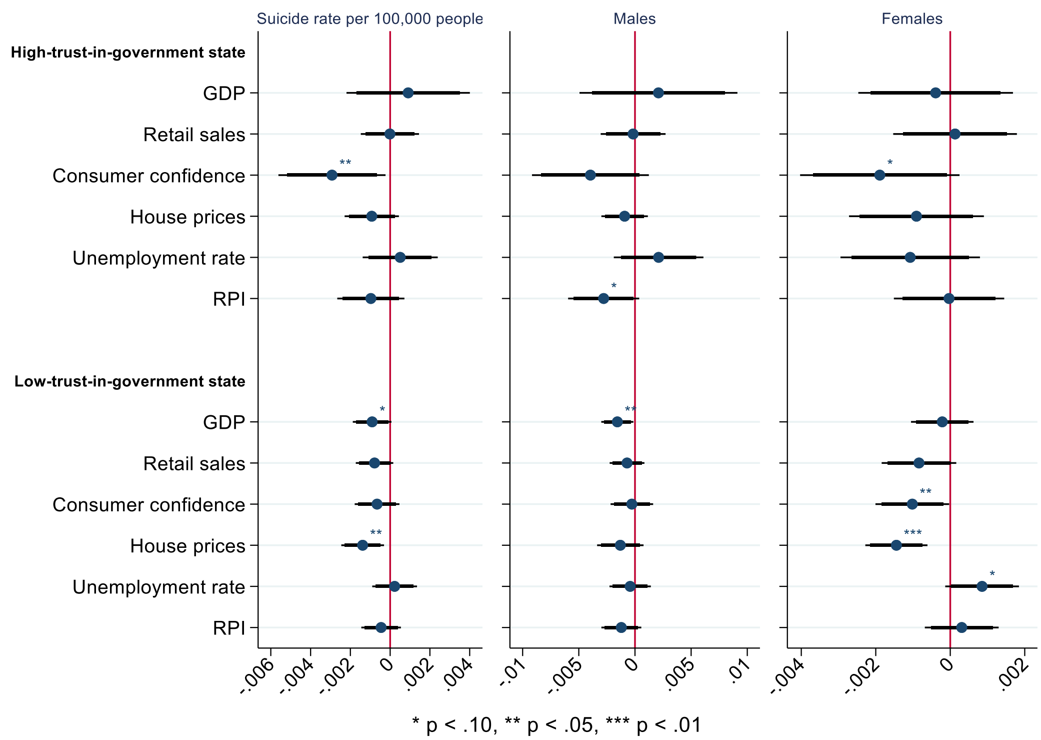


Figure A5. Time-varying responses based on the state of public trust in the British government: Debiased forecast errors for retail sales, house prices, and RPI



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