An Roinn Airgeadais
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A high frequency model of the COVID-19 pandemic in Ireland and its trading partners using time series econometrics

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Donal Smith [a], ***Luke Rehill*** [a] ***and Haicheng Shu*** [b] [1]

Abstract

The COVID-19 pandemic represents a complex challenge to policymakers from both a public health and economic perspective. It has caused a severe economic shock to both the Irish and global economy with shutdown measures implemented in most economies. This paper describes a high frequency database and model developed from both the econometric and medical literature to provide a relative measure of the path of the pandemic in Ireland and across the globe with the aim of adding to the real time evidence for policy makers. Model estimates are reported for the critical early and peak stages of the pandemic.

The pandemic is modelled as a stochastic difference equation. The logistic form is chosen as it is found to be the most practical model with the flexibility to provide daily estimates for a large set of countries on a key aspect of the pandemic, the steepness of the curve. This characteristic of the pandemic, whereby a steep rise in cases results in “flatten the curve” policy responses, is most closely associated with a suppression of economic activity. As a small open economy, it is critical for policy makers in Ireland to track developments in external demand. It is a key variable that frames scenario analysis and forecasting for government budgeting. The high-frequency database and time series model developed in this paper provides a real time relative indicator of potential economic impacts from the global spread of COVID-19 by estimating well known properties of functions.

In the early stages of the pandemic the model estimated a high value of steepness of the curve for Spain and Italy and a low level for Korea. Ireland’s measure showed a trend decline, in line with countries such as Denmark and Austria. As the situation improved in Ireland model estimates provided an early indication of a deteriorating situation in some of Irelands main trading partners indicating a more prolonged economic impact. Second wave estimates indicated lockdown measure would persist throughout 2020 in large European trading partners.

[1] a Department of Finance, Upper Merrion Street, Dublin 2, Ireland.
b School of Economics, Southwestern University of Finance and Economics, China.

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1. Introduction

The outbreak of coronavirus disease (COVID-19), first identified in China in December 2019, has now become a global pandemic. In 2020, approximately 71.5 million cases of the disease have been confirmed affecting almost all countries and territories, leading to over 1.6 million fatalities.[2] Aside from the health impact, this has also brought the world economy to a near standstill as governments introduce measures in an effort to contain the spread.

For Ireland, COVID-19 poses the single largest challenge to the economy since the financial crisis (2007-08), and is likely to have an even larger impact in the short term. The highly contagious nature of the disease has meant that the stringency of the containment measures imposed have been unprecedented in nature even compared to the previous literature on the economic impact of pandemics, (Keogh-Brown, 2010, Jonung and Roeger, 2006). Economic activity in some sectors has completely ceased, while the labour market has also been transformed from one of full employment in late-2019, to one in which unemployment reached its highest level on record (Central Statistics Office, 2020). A number of domestic institutions have estimated a severe impact on the Irish economy, McQuinn et al., (2020) (ESRI), Central Bank (2020) and Department of Finance (2020a). The estimated impacts on GDP for the year range from a -7.1 to -10.5 per cent decline depending on the type of recovery scenario assumed.[3] Ultimately an exit from the containment measures will be determined by the path of the virus, this underscores the importance of quantifying the real time dynamics of the virus.

In addition to the direct impact of measures on the domestic economy, part of the estimated downturn for Ireland stems from the weakening of the global economy as the COVID-19 pandemic has also led to lockdown measures across a substantial number of Ireland's trading partners. In their broader contagion scenario, the OECD forecast global growth to fall to 1.5 per cent in 2020, half the rate that was predicted before the pandemic (OECD 2020a). The IMF forecasts are even more pessimistic, projecting the global economy to contract sharply by 3 per cent in 2020, worse than the fall observed during the 2008–09 financial crisis. This worsening of the external environment will weigh on demand and so economic activity within Ireland. For the year as a whole, GDP will likely decline significantly in the euro area, UK and US (IMF, 2020) – with these destinations accounting for two-thirds of Irish exports. Ireland's vulnerability as a small open economy to such shocks in the global environment is well documented, a world demand shock is an important scenario in macroeconomic policy models of the Irish economy, Bergin et al., (2013, 2017), and in sensitivity analysis in framing government budgeting, Department of Finance (2018, 2019). The reliance on markets such as the UK has previously been highlighted in studies focusing on the economic impact of Brexit (Department of Finance 2016). It is thus important to not only track the path of the pandemic in Ireland but also in Irelands key trading partners and globally.

With rapid changes in the dynamics of the pandemic, the prospects of economies exiting lockdown measures can change on a daily basis. Of critical importance is the steepness/flatness of the pandemic curve, as this is related to the severity of the pandemic and so to the use lockdown measures and their associated economic implications (OECD, 2020b). The need for daily tracking across a large number of countries motivates the development of the model in this paper. In estimating the steepness/flatness daily fatalities

[2] Authors calculations based on data from the European Centre for Disease Control (ECDC) https://www.ecdc.europa.eu/en

[3] Box 5 of the Department of Finance Stability Programme provides an overview of the different recovery scenarios.

data are used as opposed to cases. Cases would give more of a leading indicator of potential future pressures on the health services. However, fatalities data are likely to be more comparable across countries than cases data and the aim is to provide estimates on the relative path of countries throughout the pandemic due to its economic implications and not to provide a predictive, medical scenarios type model as is done with SEIR models from the epidemiological literature.

The literature has already shown that stricter lockdowns go in tandem with a reduction in COVID-19-related fatalities (Conyon et al, 2020), as well as other specific restriction such as the banning of mass gatherings, international travel and workplace closures (Ahammer et al, 2020, Hubert 2020, Deb et al, 2020), all of which are likely to have a substantial economic impact. School closures have been enacted in many countries and can impact labour supply with estimates that 16-45% of parents need to take leave from work and 16-18% would experience a reduction in income under this policy response. Employing a reduced-form econometric approach, Égert et al, (2020) quantify the impact of such government interventions on disease progression and link this to the physical mobility of people, a proxy of economic activity. Bases on estimates of activity and the Oxford lockdown stringency index for a sample of 49 economies they find that a tightening of the stringency index by 10 points is associated with a 1 percentage point decline in quarterly GDP growth (OECD 2020c). Other papers have estimated the impact of COVID-19 on the economy using high frequency data from the electricity markets (Fezzi and Fanghella, 2020) or stock prices (Davis et al, 2021) and find a negative impact.

As will be discussed in the subsequent section a range of modelling approaches have been used to track the pandemic and provide evidence for policy makers. These include large simulation models from the epidemiological literature but also econometric approaches (Atkeson (2020), Acemoglu et al., (2020), Murray (2020) and Jiang, Guo, and Zhao (2020)). Econometric approaches are particularly applicable as the topics of economics and finance have always been to the forefront of high frequency and big data modelling problems (Dunbar, 2019). This paper first presents a high frequency database and summary statistics to track the dynamics of COVID-19 across countries and second presents a logistic model which has the flexibility to estimate a high volume of daily data across a large number of countries allowing an insight into countries relative dynamics with minimal computational constraints. The high frequency dataset and summary statistics where developed as throughout the pandemic a considerable volume of media attention was placed on country league tables of cumulative COVID-19 cases and fatalities which failed to make adjustments for population size or the starting point of the pandemic (Blamford et al., 2020, Beaney et al, 2020). The summary statistics described in this paper aimed to fill this void by providing policy makers with daily statistics with adjustments to improve cross-country comparability.

The time-series estimation approach is complementary to SEIR models (Golinski and Spencer, 2020b). SEIR models are used to quantify medically motivated precise interventions such as, the lifting of restriction and counterfactual estimation of the impact of these policies on the rate of transmission, hospital admissions and intensive care unit (ICU) admissions. SIER models are described in Liao et al., (2020), Cooper et al., (2020) and Acemoglu et al., (2020). These models have similarities with policy simulation models used in Governments and Central banks. They contain a large set of theory motivated equations and calibrated parameters linking key epidemiological variables. The detail involved in building and solving these models for a particular country mean that the logistic approach is complementary as it provides a flexible high-frequency cross-country comparison.

In reporting estimated results, although figures can be reported to the current date, the focus in this paper is on estimates produced at the early stages and peak of the pandemic when the figures are of most value to policy makers dealing with a very new challenge.[4] Results are provided for the full year of 2020 and include the first and second waves seen in many countries. The paper focuses on comparative, cross-country daily metrics. Descriptive statistics that track the daily cumulative total and dynamics of fatalities across a range of countries, adjusting for population size and age profile, are first presented. Model estimates of the steepness of the curve are then reported to provide a relative measure to add insight into the potential duration of lockdown measures in Ireland and its trading partners. The paper will be organised as follows Section 2 reviews the literature. Section 3 presents the data and model used. Section 4 presents the results and Section 5 concludes.

2. Literature Review

COVID-19 predictions of fatalities have largely been based on mathematical models that capture the probability of moving between states from susceptible to infected, before either a recovered state or a fatality (SIR models).[5] How an epidemic plays out over time is determined by the transition rates between these three states, while the rate at which susceptible individuals become infected is dependent on the number of individuals in each of the susceptible and infected compartments of the model.[6] In general, these models assume random mixing between all individuals in a given population.[7] SIR models can account for a range of alternative estimates of key parameters, such as the number of contacts per individual and the transmissibility of the disease. This allows them to be used for counterfactual scenario analysis where lockdown strategies can have a direct impact on the number of contacts per individual and predicted infections. The building blocks of SEIR models used in COVID-19 analysis contain coupled non-linear ordinary differential equations for Susceptible, Infective and Removed groups. The models are solved numerically with the theoretical structure allowing counter factual policy scenario analysis which would not be possible in a purely econometric approach.

A more aggregate strategy is to focus on modelling the empirically observed COVID-19 population infection or fatalities curves, the latter of which directly reflect both the transmission of the virus and the case-fatality rates in each community. Indeed, daily fatalities are likely more accurately reported than cases in settings with limited testing capacity. Logistic models can be used to provide a simple representation of the evolution of infection numbers, hospital admissions and fatalities from a pandemic by fitting a curve to the available series. These have been commonly used to model outbreaks as they are able to capture the initial slow growth of a pandemic, followed by a period of rapid growth, followed by a tapering off (Baldwin, 2020).

Early results using these types of models have shown a high degree of accuracy in predicting the evolution of the COVID-19 outbreak in Wuhan (Batista, 2020). This was also the case when applied to other regions in China, while outperforming the use of other mathematical models in its fit for cases and fatalities (Jia et al, 2020). Logistic models have also been used with empirical data from Costa Rica, Italy, Spain and the US (Villalobos-Arias, 2020), obtaining

[4] Estimates in this paper are correct as end 2020.
[5] SEIR models are similar but also include an 'exposed' group.
[6] Atkeson (2020) introduces a simple SIR model of the progression of COVID-19 in the US.
[7] This can be seen as one of the oversimplifying assumptions given in human social structures the majority of contact is within limited networks (Tolles, 2020)

a high degree of fit in each case. In an attempt to forecast extreme scenarios model parameters were obtained from South Korea and Italy, two developed countries which have had very different experiences in the pandemic, in order to generate a range of forecasts for daily infections in the state of Utah (Queadan et al, 2020).

Logistic-type models have the benefit of being relatively simple, flexible and can be updated quickly to process data released on a daily basis. They can also be used to predict the point of inflection in the curve, or turning point, which is when the number of daily observations in cases or fatalities will have peaked and thereafter start to decrease. This approach has been taken to track the progression of the COVID-19 outbreak in the UK in terms of daily cases and fatalities announced, and to estimate that a corner had been turned (Golinski and Spencer, 2020a & 2020b). We follow the same curve fitting approach in this paper.[8] It is important to note that the model takes an econometric approach and does not predict the rate of transmission which is a key variable from a public health policy perspective.

3. Data, model and estimation

The data used is taken from the European Centre for Disease Prevention and Control (ECDC). This comprises daily data on cases and fatalities covering 184 countries beginning on the 31/12/2019. Fatalities data is selected for estimation as there are considerable cross-country differences is testing coverage and guidelines as compared to cases (Irish Times, 2020). Even though the fatalities data may be more consistent it should be noted that this is still not always directly comparable as countries have differed in the reporting of COVID-19 fatalities.[9] The World Health Organisation guidance on the definition of a COVID-19 death was introduced in April 2020, well into the first wave of the pandemic, at this stage many countries had introduced differing national level guidance. In Spain fatalities were only counted if there was a positive test for COVID-19 and only hospital deaths registered despite a significant volume of fatalities in care home settings. This contrasts with Belgium where fatalities were counted even for suspected COVID-19 cases and care home fatalities were included (Beaney et al., 2020). In the UK the Department of Health and National Health Service counted fatalities if there was a positive test whereas the Office for National Statistics included fatalities where COVID-19 was mentioned anywhere on the death certificate (Beaney et al., 2020). A further complication is that at the beginning of the pandemic there was no standard method for diagnosing COVID-19.

The dynamics of fatalities across countries are modelled by a stochastic difference equation. There are a number of functional forms this distribution can take with selection depending on the shape of the distribution and the aims of the estimation. Commonly used functions are logistic, beta and gamma distributions. In this paper the general logistic function is used:

$$F(t) = \frac{\beta_1}{1 + e^{(\beta_2 - \beta_3 * t)}} \qquad (1)$$

Time is given by $t, F(t)$ is the cumulative number of fatalities at time t and β are the parameters estimating key features of the curve, level, intercept and slope. In the case of modelling COVID-19 fatalities the level, β_1, is the final total number of fatalities. This functional form can

[8] A Gompertz curve or other functional form specifications can provide a better fit to the data for some countries however in the early and peak stages of the pandemic, which is the focus of this paper, there is not a substantial improvement over the logistic model.

[9] The prime aspect here was some countries were not reporting COVID-19 fatalities that occurred outside of hospitals (i.e. nursing homes and long term care facilities).

match the dynamics seen in Figure 1. The model is flexible enough to fit the distribution at both the early and late stages of the pandemic. For estimation the model is discretized and an error term $\epsilon_t \sim N(0,1)$ is added. Estimation is in differences given the issues with levels data in time-series (Sims, 1980). The discreet, differenced version of the model is given as:

$$F_{t+1} - F_t = rF_t(1 - F_t/\beta_1) + \sigma[rF_t(1 - F_t/\beta_1)]^{\sigma}\epsilon_{t+1}$$

$F_{t+1} - F_t$ is the number of new fatalities at any time t.[10] The right hand side of the equation represents a bell-shaped function which the will be fit to the daily fatalities data matching the dynamics seen in Figure 3. As discussed in Golinski and Spencer (2020a), to ensure a bounded process the model contains a volatility term employing techniques from the finance literature (Cox et al., 1985).

One reason studies in the literature employ beta and gamma distributions is they are primarily interested in forecasting total cases and fatalities with underlying data that displays a pronounced upper skew (Golinski and Spencer 2020b). This is of benefit as one of the characteristics of the logistic distribution is that it is symmetric. This would lead to an underestimate of total fatalities and cases when applied to real world data. A beta and gamma form of the difference equation would respectively be:

$$F_{t+1} - F_t = rF_t^{\alpha}(1 - F_t/\beta_1)^{\mu} + \sigma[rF_t^{\alpha}(1 - F_t/\beta_1)^{\mu}]^{\sigma}\epsilon_{t+1}$$

$$F_t - F_{t-1} = rF_t^{\alpha}\exp(-\gamma F_t) + \sigma[rF_t^{\alpha}\exp(-\gamma F_t)]^{\sigma}\epsilon_{t+1}$$

The additional parameters in these functions allow the models to fit the upper skew seen in fatalities data (Figure 3). The beta function has two additional parameters and setting $\alpha, \mu = 1$, simplifies to the logistic model. The gamma model has one fewer parameters than the beta distribution but can still fit the skewed distribution. These model outperform the logistic model in-terms of out-of-sample forecasting of the total number of fatalities (Golinski and Spencer 2020b). The logistic model is however still chosen in this paper as the aim is to provide a flexible high frequency estimate of a specific mathematical property of COVID-19 fatalities data, the steepness of the curve, and to implement this across a large set of countries. This property is most closely associated with economic disruption, a rapid increase in numbers leads to “flatten the curve” policies and these have a consequence of suppressing economic activity. We find a higher degree of variance in steepness estimates from the gamma and beta distributions. While these models perform better on a single data set for forecasting total fatalities the logistic model has a much greater degree computational flexibility for high frequency data.[11] For comparison and robustness beta and gamma estimates are provided for Ireland and for the second wave.

4. Results

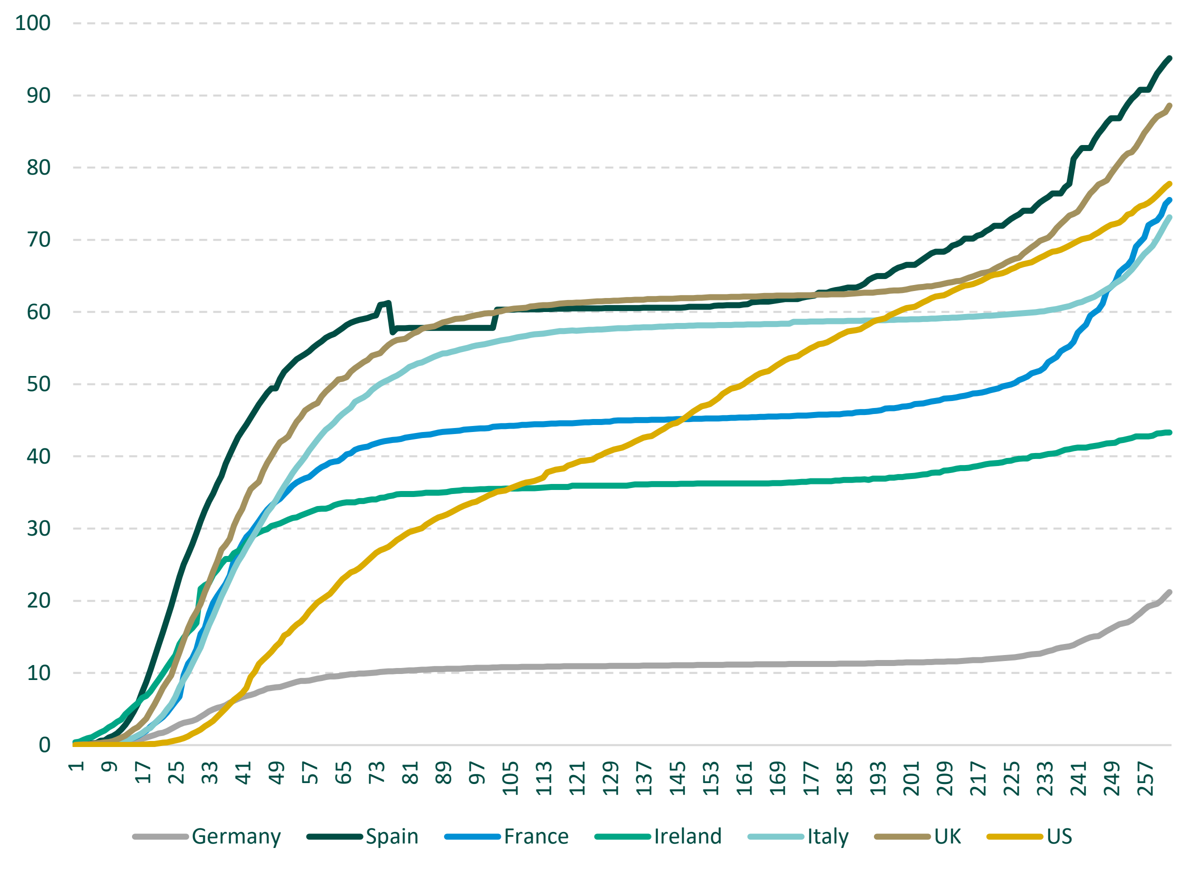
Fatalities from the virus have displayed a very different dynamic across countries (Figures 1, 2, 3 & 4). These figures show comparative measures throughout 2020. The pandemic changes rapidly over time and there is a distinct first and second wave in most countries (Figures 1-3). The figures presented give a sample of the daily summary statistics produced throughout the pandemic. The data set contains 61,901 data points for the year 2020. In the figures the growth rate and levels of the data are aligned to give countries a common starting point, e.g. greater

[10] $r = -(\beta_2 - \beta_3)$. The value of σ is calibrated at 0.75 as in Golinski and Spencer (2020b).

[11] The standard deviation of the steepness estimates are 0.03 and 0.04 for the logistic model for Austria and Korea respectively while for the gamma model they are 4.0 and 1.1.

than 10 fatalities recorded and converted to fatalities per 100,000 of population, to facilitate cross-country comparison as countries entered the pandemic at different points in time. Reflecting the differential spread of the virus Italy reached at least 10 fatalities on the 26/02/2020, in Ireland this was on the 27/03/2020 and for the UK the 14/03/2020. This is the starting point for Figures 1-3 with the x-axis recording the number of days beyond this point. Figure 2 adds a demographic aspect to the summary statistics by reporting fatalities per 100,000 of the over 65 population. This reflects COVID-19's disproportional impact on older cohorts and the variation in age structure across countries, in Ireland 14% of the population are over 65 compared to 23% in Italy.[12]

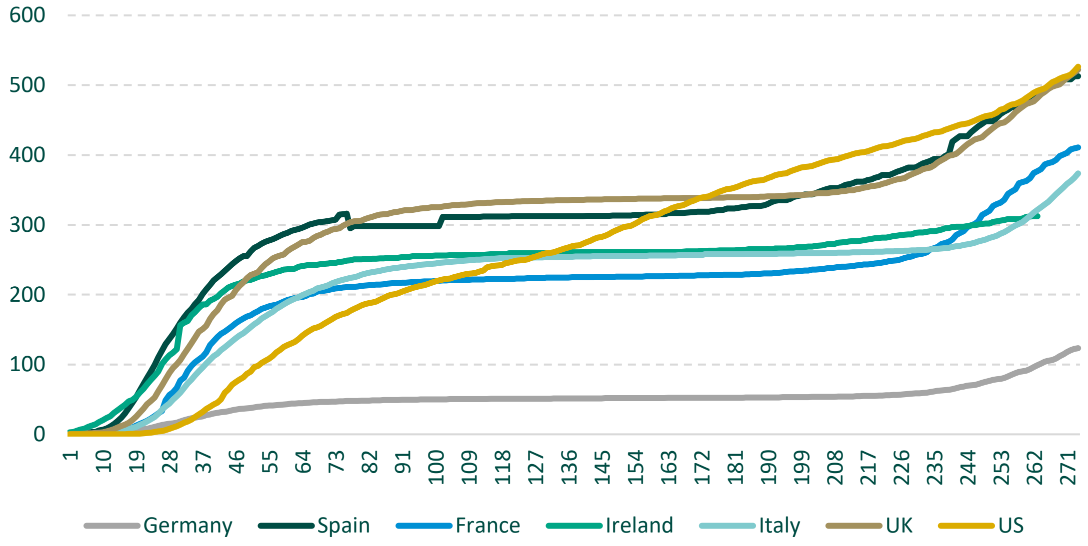
Figure 1: Fatalities per 100,000 in days after 10 fatalities recorded in each country



Source: Authors calculations based on ECDC data.

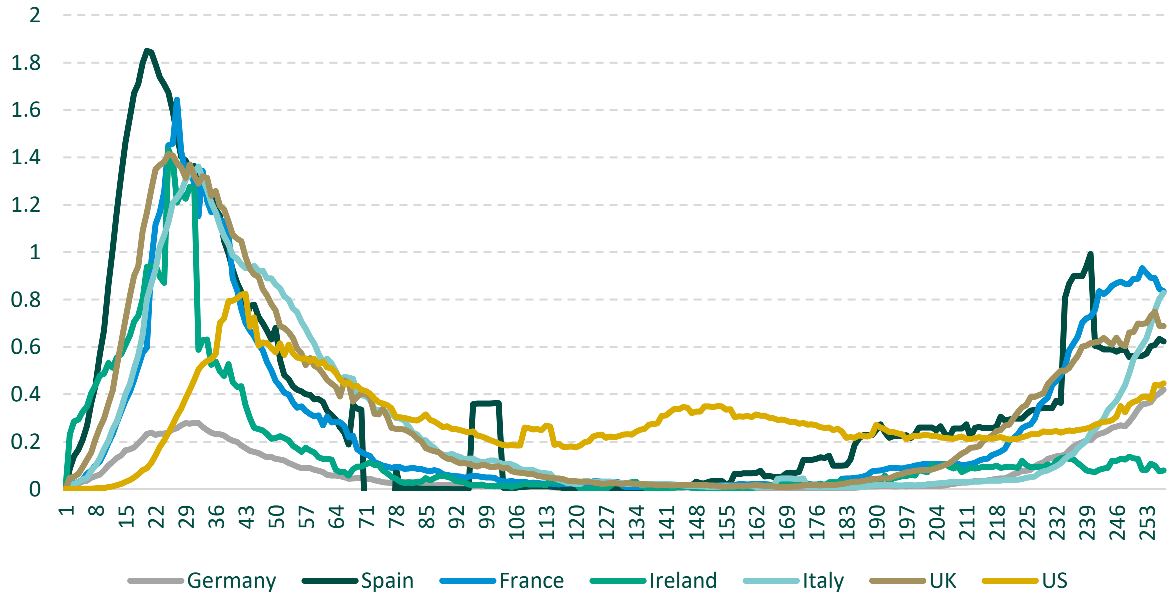
[12] There are many other control factors that could contribute to cross-country variation in fatalities in addition to age structure. Comorbidities such as the prevalence of cardiovascular disease, cancers, diabetes and chronic lung diseases appear to greatly increase the mortality risk (Sorci et al., 2020). This complication can be seen in that although the United States has a younger age profile than many other countries it has more comorbidities compared with other countries (Bilinski and Emmanuel 2020).

Figure 2: Cumulative fatalities per 65+ population



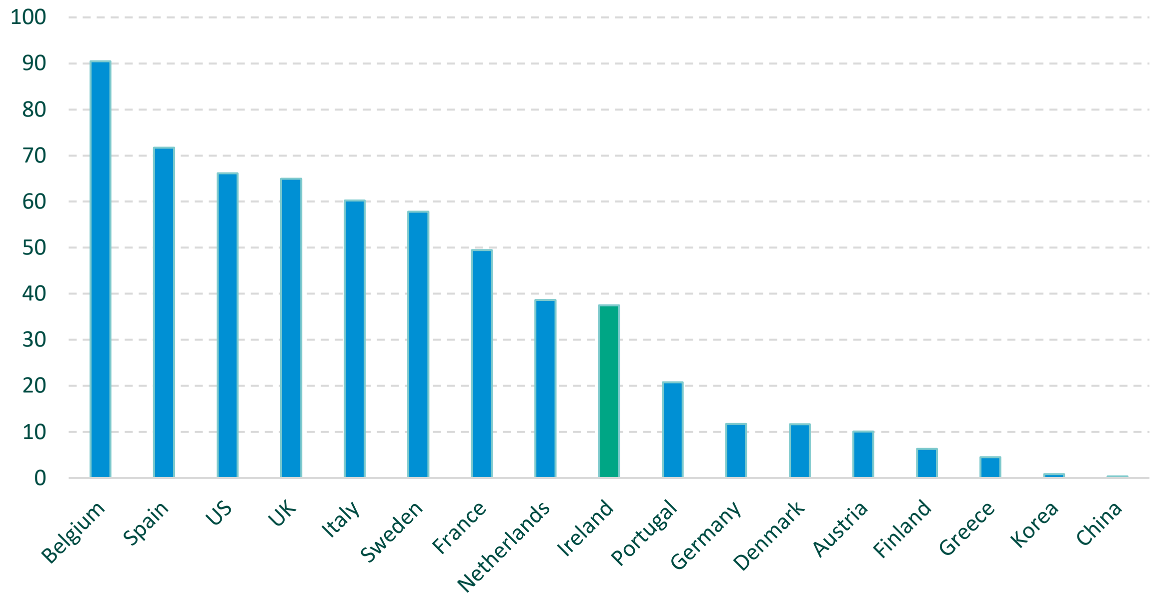
Source: Authors calculations based on ECDC data.

Figure 3: Seven day average change in fatalities per 100,000 in days after 10 fatalities recorded in each country



Source: Authors calculations based on ECDC data.

Figure 4: Latest five day average of fatalities per 100,000 (as of 14/12/2020)



Source: Authors calculations based on ECDC data.

The model is applied to a rolling sample of daily data from 15 observation up to the end of each wave for each country. The data set covers all of 2020 with a sizable number of countries displaying two distinct waves of the pandemic over this period (Figure 3). As the aim is to provide a relative measure associated with the pandemics economic consequences the sample is split and the model estimated from the beginning of each of the waves. The brake point to begin the second sample is taken as the 01/09/2020 as September had the first week of constitutive increases in fatalities across a sample of countries since the first spring-early summer wave. Throughout the pandemic the data program allowed the model to be run for 184 countries and provided summary statistics and estimates on a daily basis. The first observation is taken as when a country recorded at least 10 fatalities for the summary statistics and 5 for the model estimation. While not a causal analysis, and relying on distributional assumptions, this data driven model can give some indication of countries relative position in moving through the pandemic. The logistic function provides a close description of the pandemics dynamics. The fitted and actual values from the estimation of equation 2 for China, Ireland, Italy and Spain are shown in Figure 5. There is a good fit of the model and actual data for cumulative fatalities. These countries are chosen as a comparison to the Irish model as China has experienced the virus for the longest time period and Italy and Spain witnessed two of the most severe outbreaks in Europe. The fitted values show that the logistic model provides a flexible model that can accurately capture the shape of the virus at all stages and profiles, early in Ireland, severe in Italy and Spain and at the final stages in China.

A key element leading to shutdown measures is the risk of pressure being placed on medical services by a rapid increase in the spread of the virus. Rolling estimation of the flatness or steepness of the underlying function can provide an indicator over time and across countries of entering a lockdown scenario (Figure 6). The models estimates show that in the early stages of the pandemic Korea, which has managed to avoid severe lockdown measures, has a low number and is well below the estimate for Italy, Spain the UK and US. This can be interpreted as indicating that Korea was far less likely to see a need for “flatten the curve” policies as opposed to Italy and Spain which measured a steep rise in fatalities. A higher value of this parameter in the graph indicates a much more steep logistic function and so more pressure on domestic medical services. The situation in important trading partners, the UK and US, was estimated as deteriorating over time indicating the potential for a more prolonged economic impact. Ireland’s number has shown a trend decline and is closer to the estimates seen in Denmark and Austria than severely impacted countries like Spain and Italy. Denmark and Austria were among the first European countries to lift lockdown measures after the first wave.

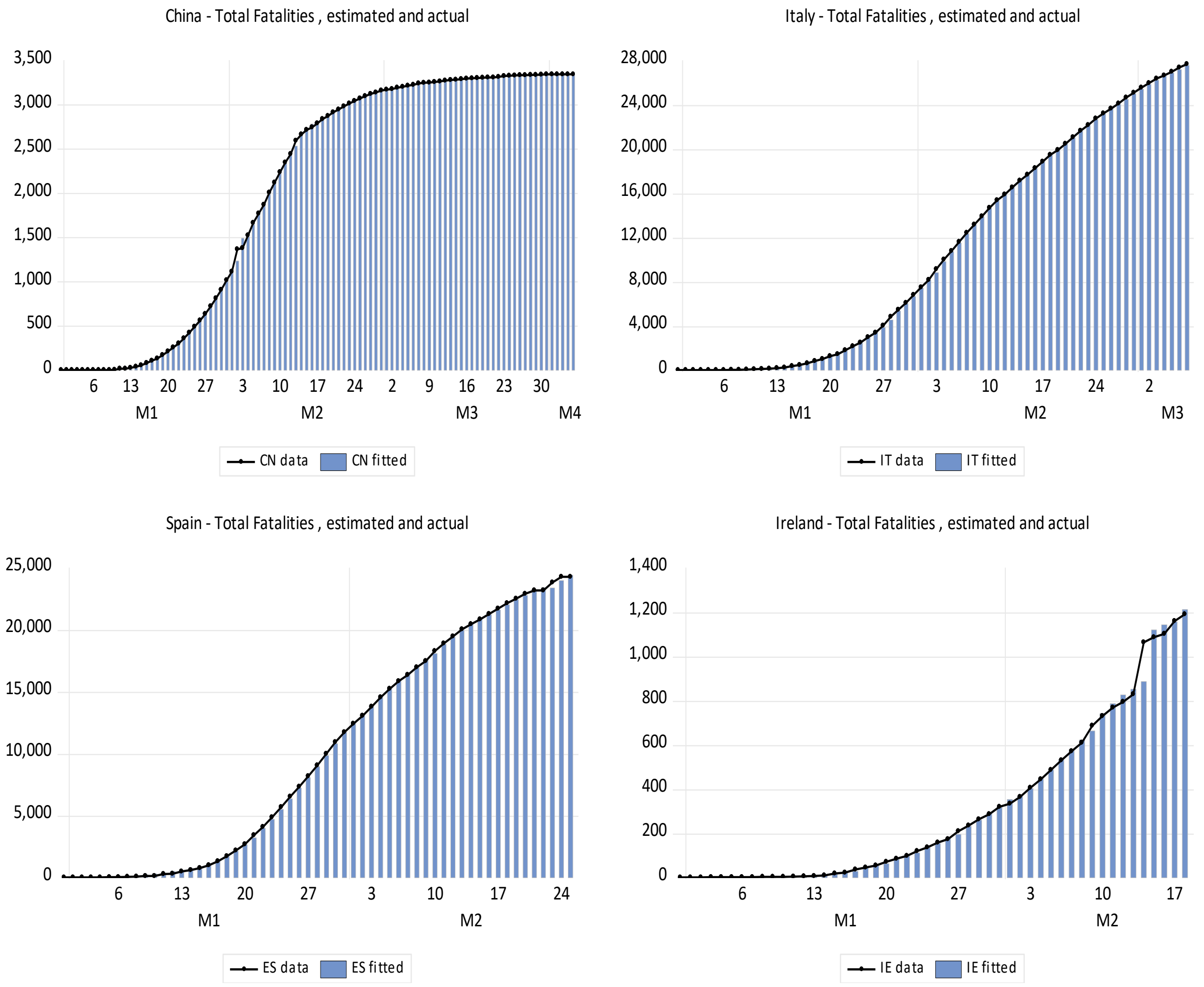
The flattening of the curve estimated in Ireland highlights the value of model based estimated as this can be seen at a time when fatalities were increasing. The cross-country estimates can be used to construct and illustrative scenario such as a comparison of a situation where Irelands curve had not flattened to this extent and had instead evolved in line with that of Spain. This illustrative comparison shows that if the steepness of the curve in Ireland had been at the same average level as Spain 1,000 fatalities may have been reached 17 days earlier than actually observed. This would have implications for pressures on the medical service and would likely have prolonged shutdown measures. The turning point can be approximated by forecasting of model parameters. The results for the turning point estimates are: Ireland - last week of May; UK - Last week of April; Spain - 2nd week of April. These forecast numbers should be interpreted in the context of the caveats outlined.

As discussed in section 2 there are a number of possible specifications of the difference equation. For robustness the gamma and beta models are estimated for Ireland for the rolling estimation to track the steepness of the curve (Figure 7). The gamma and beta models report higher values for the parameters and do show the same declining trend however in these models the volatility of the rolling estimates is high. This difficulty in estimating certain parameters reliably is also noted in Golinski and Spencer (2020b). The logistic model has the advantage in producing stable high frequency estimates. For a further comparison the second wave estimates for the logistic, beta and gamma distribution for a set of countries are reported in Appendix Table 1.[13] For Ireland the gamma model has the best fit however the difference is not as pronounced as for other countries with a more obvious skew and is quite close to the fit of the beta and logistic models. Comparing the models fit to those for the first wave in Golinski and Spencer (2020b) there is less difference in model fit across countries indicating the skew of the distribution is less in the second wave. This can be seen in particular in the case of Italy where the logistic, beta and gamma models have a very similar fit for the second wave whereas they diverged considerable in the first wave. The results for the United Sates for all 3 models are spurious as there is no clear break between first and second waves in the sample but rather a long continuous first wave throughout 2020 (Figure 1).

Given the close fits of the three models, the volatility of the steepness estimates and that the main motivation for using skewed distribution is improving forecast estimates of total fatalities, the logistic model is used for second wave steepness estimates across the sample of countries (Figure 8). The US is excluded as there is no clear break for a second wave. Spain Italy and the UK had the high values for steepness and the UK figures surpassed that of Spain half-way through the sample. These figures were higher than those reported for countries such as Sweden which avoided stringent lockdowns and Ireland which had a relaxation of measures towards the end of 2020. This indicated many of Ireland trading partners would continue to have a risk of lockdown measures towards the end of 2020.

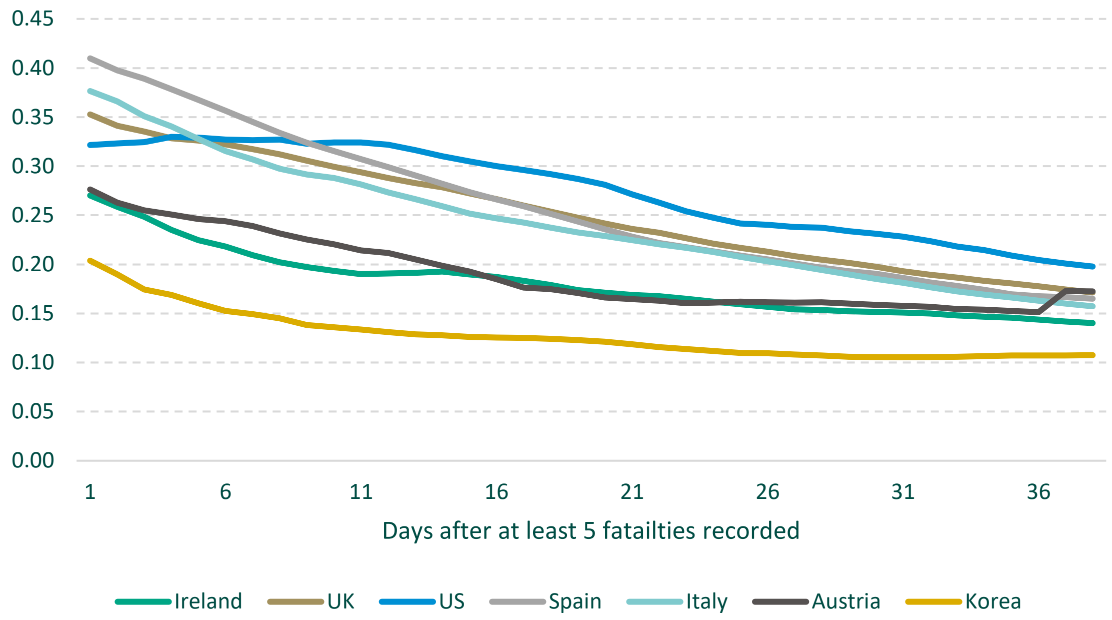
[13] Estimates can be compared with first wave estimates reported in Golinski and Spencer (2020b).

Figure 5: Estimated and actual fatalities in days after first 5 fatalities recorded in each country.



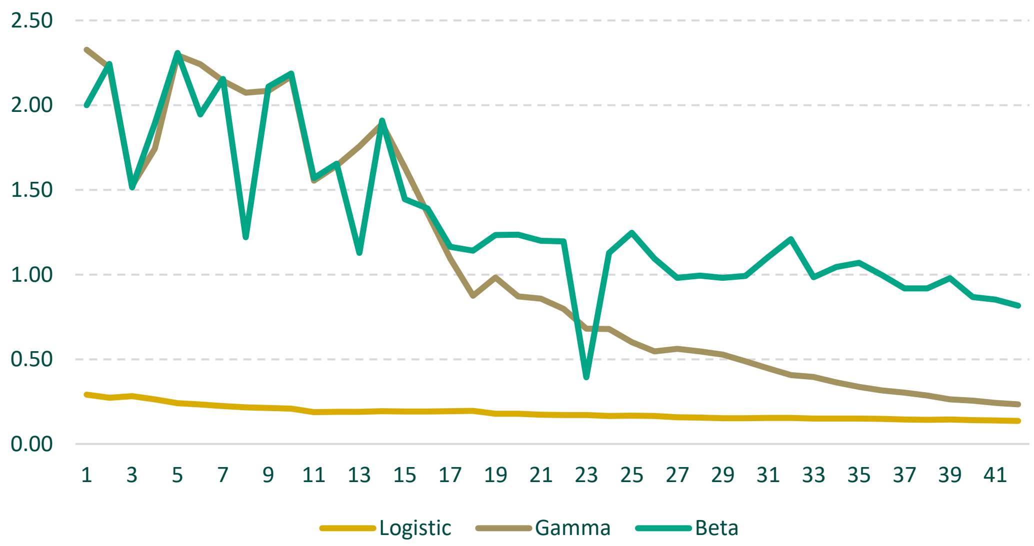
Source: Authors estimations using ECDC data

Figure 6: Three day average of the measure of steepness/flatness over time. Rolling estimation for all countries beginning for N=15 after at least 5 fatalities were recorded[14].



Source: Authors estimations using ECDC data

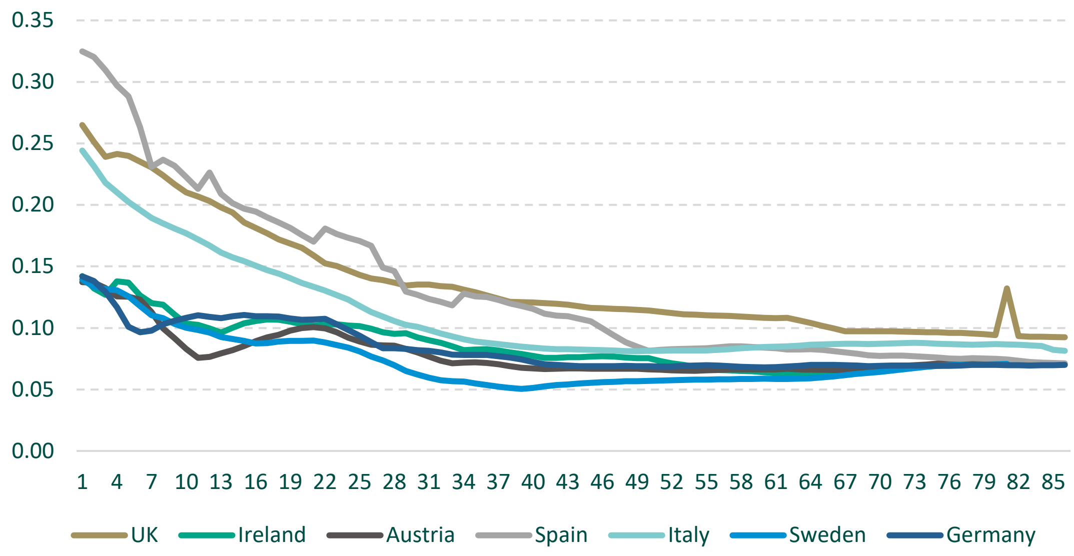
Figure 7: Ireland parameter estimates – Logistic, beta and gamma



Source: Authors estimations using ECDC data

[14] Date from which at least 5 fatalities were recorded: Austria - 20th March, Denmark – 20th March, Spain – 7th March, Ireland – 24th March, Italy – 25th February, Korea – 23rd February, UK – 11th March, US – 3rd March.

Figure 8: Three day average of the measure of steepness/flatness over time. Rolling estimation for all countries beginning for N=15 after at least 5 fatalities were recorded – 2nd wave



Source: Authors estimations using ECDC data

5. Conclusions

The COVID-19 pandemic has spread rapidly across the globe and caused considerable challenges for policy makers. A key component in determining the economic impact is the path of the pandemic in Ireland and its trading partners. In quantifying this there are a wide range of modelling approaches available from the medical and economic literatures which can be used to provide insights on the spread of the pandemic. In this paper we present both a high frequency cross-country set of summary statistics and a range of time-series econometric models. This approach is taken as data modelling methodologies employed in economics and finance are well suited to handling high frequency and large datasets. Quantifying the path of the pandemics is important as a rapid increase in the spread of COVID-19 is associated with "flatten the curve" policy responses. While these have been shown to be effective in reducing cases and fatalities they also have a consequence of supressing economic activity. The summary statistics presents in this paper give daily updates to policy makers on the evolving situation globally and the model estimates allow deeper insights to be drawn on the underlying relative dynamics. Combined these provide an early indication of changes in the COVID-19 situation across Ireland main trading partners and so provide a daily gauge on the imposition and duration of lockdown measure and their associated economic impact. As a small open economy Ireland is particularly sensitive to adverse changes in the external environment.

We construct a daily data set of COVID-19 fatalities of 184 countries and apply an econometric model to track the relative evolution of the flatness/steepness of the pandemic curve in a subset of countries for both the first and second wave in 2020. In the paper the summary statistics and estimates are presented for the early stages and peak of the pandemic as this is when this information was most critical for policymakers. The summary statistic indicators revealed a wide divergence in the dynamic of the pandemic. The rapidly evolving nature of the pandemic necessitated the use of high frequency data techniques. The model is complementary to those used for public health policy as while it does not predict the rate of transmission it can provide relative measures across a large set of countries.

The flatness/steepness of the pandemic curve is a key feature as a steep curve, although not an exact measure, provides some indication of the risk of a situation where there may be an excessive strain on the health service and so a continuation of lockdown measures. Estimates of this flatness/steepness parameter are provided for a number of countries for both the first and second wave. The results show consistent low estimates for Korea and high values for Spain and Italy that reduce over time. The model estimates that there has been a flattening of the curve in Ireland over time, relative to other countries. This trend emerged even as the number of fatalities was increasing. This estimate showed that Ireland was moving into line with countries such as Denmark and Austria which had avoided the very sharp rise to peak fatalities seen in other countries. Early in the pandemic as the situation in some of Irelands continental trading partners appeared to be improving the US and UK began to deteriorate with implications for external demand, suggesting a more prolonged economic impact. An illustrative comparison shows that if the steepens of the curve in Ireland had been at the same average level as Spain 1,000 fatalities may have been reached 2.4 weeks earlier. Second wave estimates indicate that this wave would have less of a skewed distribution than the first and that lockdown measure would persist throughout 2020 in large European trading partners.

In comparing fatalities data across countries, the results should be interpreted with caution as there are many potential control variables, comorbidities, age profiles, the timing of the virus, early stage versus later when medical responses have progressed. There are also caveats due to variation in the definition of a COVID-19 fatalities across countries. Mutations of the virus and multiple re-infection would also result in a stochastic equilibrium which would require an alteration of the modelling approach. Since the pandemic has begun and because of its severe economic impact a range of measures have been developed to try to provide a time-varying measure of lockdowns, such as the Oxford stringency index. A possible area of development would be to link the analysis in this paper to these newly emerging measures.

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Appendix

Table 1

Model	Log-lik	r	β1	α	β	sigma
			Sweden			
Logistic	-291.6	0.07	2,219	-	-	0.91
		0.01	*162*	-	-	*0.07*
Beta	-291.2	0.02	2,351	1.23	1.62	0.89
		0.01	*278*	*0.07*	*0.27*	*0.07*
Gamma	-283.4	0.02	1.27	11.31	-	0.96
		0.01	0.10	2.42	-	0.08
			Ireland			
Logistic	-227.3	0.06	395	-	-	1.49
		0.01	18	-	-	0.18
Beta	-219.1	0.63	346	0.42	0.16	1.25
		0.28	*0.04*	*0.09*	*0.04*	*0.13*
Gamma	-217.3	0.94	0.31	3.35	-	1.30
		0.87	*0.26*	*22.05*	-	*0.14*
			UK			
Logistic	-521.4	0.09	26,945	-	-	1.28
		0.00	*703*	-	-	*0.10*
Beta	-502.4	0.34	29,141	0.82	0.73	0.94
		0.05	*9,357*	*0.02*	*0.50*	*0.07*
Gamma	-497.7	0.30	0.85	0.46	-	0.98
		0.07	*0.03*	*0.07*	-	0.07
			Germany			
Logistic	-464.9	0.07	24,358	-	-	1.37
		0.00	*3737*	-	-	*0.11*
Beta	-465.2	0.07	12,501	0.98	0.22	1.34
		0.02	*46*	*0.04*	*0.10*	*0.11*
Gamma	-462.0	0.06	1.04	0.64	-	1.39
		0.02	*0.05*	*0.21*	-	*0.11*
			Spain			
Logistic	-697.6	0.07	19,333	-	-	4.87
		0.01	*354*	-	-	*0.59*
Beta	-674.2	0.44	18,530	0.74	0.54	4.37
		0.13	*0.41*	*0.04*	*0.06*	*0.59*
Gamma	-651.1	2.11	0.55	0.37	-	3.71
		1.38	*0.09*	*0.25*	-	*0.38*
			Italy			
Logistic	-523.4	0.08	36,503	-	-	1.22
		0.00	*1211*	-	-	*0.09*
Beta	-522.7	0.15	32,718	0.92	0.61	1.11
		0.03	*4031*	*0.03*	*0.24*	*0.08*
Gamma	-518.1	0.13	0.95	0.41	-	1.16
		0.03	*0.03*	*0.05*	-	*0.09*
			Austria			
Logistic	-341.7	0.07	5,879	-	-	1.07

		0.01	*692*	-	-	*0.09*
Beta	-343.2	0.07	3,631	0.98	0.29	1.04
		0.02	*21*	*0.05*	*0.09*	*0.09*
Gamma	-338.0	0.06	1.04	2.65	-	1.10
		0.02	*0.07*	*0.88*	-	*0.09*
			US			
Logistic	-902.0	0.08	133,312	-	-	8.20
		0.01	*5,702*	-	-	*1.08*
Beta	-818.2	68.99	40,655,241	0.26	0.00	3.07
		0.00	*0.00*	*13588488603*	*13588488603*	*0.00*
Gamma	-808.8	5.24	0.58	0.10	-	3.75
		3.05	*0.07*	*0.04*	-	*0.53*

Note: Estimates of the logistic, beta and gamma models. Standard errors are reported in italics.