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RESEARCH ARTICLE

Excess Deaths and Excess Covid Booster Vaccine Doses – are they related?

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ABSTRACT

This paper features an analysis of Organisation for Economic Co-operation and Development (OECD) country level data generated by the COVID-19 pandemic as revealed in data related to booster vaccinations, excess deaths, populations, infections, recovered cases, and tests, for a sample of 38 countries, plus measures of their policy responsiveness and relative preparedness, including various other indicators of trust, stringency and Gross Domestic Product (GDP) per capita. The paper uses OECD weekly data on excess deaths. The data on COVID-19 vaccine boosters administered was obtained from ourworldindata.org, the assessment includes measures of GDP per capita, and indices of country specific trust levels, the cumulative data set is taken from the Worldometer data source. The Global Health Security (GHS) Index and Oxford Stringency Index (STR) are used as policy benchmarks. Other indicators used include GDP/capita, Trust, and Personal Trust Indices from the OECD. Cross sectional regression analyses suggest that COVID-19 booster vaccines explain between 69 and 79 per cent of the variation in excess deaths in OECD countries as captured by excess deaths in the first week or averaged across the first three months of 2023. An adaptive lasso technique was used to screen the explanatory variables in multivariate regression analysis. This analysis suggested the addition of either the GHS or Stringency indexes, plus a version of the Trust Indices, but none of these added much to the explanatory power of the regressions which were dominated by the contribution of the measure of vaccine boosters. The results suggest a strong association between excess deaths and booster vaccinations across this sample of OECD countries.

Keywords: COVID-19, excess death rates, booster vaccinations, test regimes, relative performance, GSH Index, Stringency Index, Policy Indicators, Trust levels.

1. Introduction

The goal of this paper is to assess possible factors causing excess deaths, which appear to be pervasive in many countries after the COVID-19 pandemic, and to analyse whether excess deaths, as revealed in OECD statistics, can be attributed to excessive vaccine booster doses or to other potential factors.

Excess deaths refer to the number of deaths from all causes measured during a crisis, above what could be observed under 'normal' conditions. The excess mortality indicator takes the number of people who died from any cause, in a given period, and compares it with a historical baseline from previous years, in a period that was not affected by the COVID-19 pandemic.

1.1 Background

The outbreak of the SARS-CoV-2 virus that causes the COVID-19 disease was first detected in Wuhan, the capital city of Hubei Province, China, and reported to the World Health Organization (WHO) office in Wuhan on 31 December 2019. On 30 January 2020 WHO declared a public health emergency of international concern over the global outbreak of COVID-19 and subsequently over 7 million deaths were reported to the organisation.

In May 2023 the WHO's emergency committee determined that COVID-19 should now be considered an established and ongoing health matter no longer constituting a public health emergency.

1.2 Excess deaths

In June 2023, a month after the WHO declared the end to the COVID-19 public-health emergency, excess mortality in the EU stood at 2.5 % above the baseline, a slight decrease compared with May 2023. The situation varied greatly across the EU given that nine EU Member States recorded no excess deaths, yet over half of the EU Member States recorded excess deaths. The most affected being Ireland, the Netherlands and Finland with excess mortality rates between 13.6 % and 14.4 %.

The sample used in this study features the relatively wealthier OECD countries, yet these countries appear to be facing a post-pandemic excess death conundrum. Paradoxically, greater caution and vaccine promotion, may have led to worse outcomes! This is one of the issues explored in this study.

1.3 Data sources

The study uses OECD weekly data on excess deaths sourced from https://stats.oecd.org/index.aspx?queryid=104676#. This provides estimates of mortality (by week), for OECD countries for the period 2020 – 2023. The study will use data for the first week of 2023 and an average of data for the first 12 weeks of 2023 as measures of excess deaths (ED) and (AVED).

The study also uses data on COVID-19 vaccine boosters administered as obtained from ourworldindata.org, at their website; https://ourworldindata.org/grapher/cumulative-covid-vaccine-booster-doses. This provides a measure of the total number of vaccine booster doses administered. Booster doses are defined as being doses administered beyond those prescribed by the original vaccination protocol. The metric (CB) used in this study only features a measure of vaccinations administered above the minimum requirement.

This is used in conjunction with data used in a previous study by Allen (2023), which related to deaths, populations, infections, recovered cases, and tests, plus measures of GDP per capita, and indices of country specific trust levels[1]. The cumulative data set is taken from the Worldometer data source. The GHS Index and Oxford Stringency Index are used as policy benchmarks. Other indicators used include GDP/capita, Trust and Personal Trust Indices from the OECD.

The analysis will use OLS in cross-section. One of the problems encountered is that some countries have stopped collecting official statistics at the end of 2022. Most of the data will reflect the position at the end of 2022 or at the beginning of 2023. The measure of cumulative booster vaccine doses is a measure reflecting the position at this point in time. The excess deaths in the preliminary analysis in this proposal reflect the recorded statistics in OECD countries in the first week of 2023. This is augmented by a metric reflecting the average excess deaths over the first 3 months of 2023, given that this data was available at the time of writing.

The topic is a rapidly moving one, in that the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was affected by mutations, leading to new variants of the virus. Some of these variants were classified as variants of concern (VOC), such as Alpha, Beta, Gamma, Delta, and Omicron. VOC are characterised by increased human-to-human transmissibility.

Government responses to the pandemic varied enormously and attempts were made to capture them by the creation of indices.[2,3]. The Blavatnik School of Government at the University of Oxford introduced the Oxford COVID-19 Government Response Tracker (OxCGRT), to provide a systematic way to track government responses to COVID-19 across countries over time.

The value of the index on any given day in any given and country comes from the average of nine sub-indices (school closures, workplace closures, cancelation of public events, restrictions on gathering size, closure of public transport, stay at home requirements, restrictions on internal movement, restrictions on international travel, and public information campaign), each taking a value between 0 and 100.

Gostin, Hodge Jr., and Wiley (2020) analyzed the response to COVID-19 and suggest that a fine balance is required between individual rights and liberty, and public health concerns[4].

One of the aims of the current study is to assess whether relatively more stringent policies, in the form of relatively aggressive booster vaccine policies, led, to a greater subsequent incidence of excess deaths. McAleer refers to the GHS Index and this index is used in this study as an indicator of pandemic readiness[5, 6].

In 2021 the Nuclear Threat Initiative and the Johns Hopkins Centers for Health Security, and Bloomberg School of Public Health in collaboration with sponsors the Economist, and the Bill and Melinda Gates Foundation, produced an updated version of the GHS (Global Health and Security Index). A second version of the Index was released in December 2021[5].

The Index assigns the highest scores to countries with the most extensive capacities to prevent and respond to epidemics and pandemics. The United States was ranked first in both the 2019 GHS Index and in 2021.

However, the potential to meet a crisis does not necessarily translate into effective action. The Trust Indices were taken from the 'Our World in Data' website, https://ourworldindata.org/ trust. The OECD Guidelines on Measuring Trust suggest that trust can be viewed as a person's belief that another person or institution will act consistently with their expectations of positive behaviour.

These are used in this study to explore whether indices of trust capture the willingness of the public to embrace booster vaccine beyond the levels originally mandated by the government in that particular OECD country.

Measures of GDP per capita are also adopted to see whether relatively wealthier countries OECD had higher booster vaccine policies related to COVID-19.

The paper is divided into five sections, the introduction is followed be a review of previous work on the topic in section 2, section 3 introduces the sample and methods adopted in the study, section 4 presents the results, whilst section 5 provides a discussion and section 6 concludes.

2. Previous work

Allen and McAleer analysed the European and global spread respectively, of the SARS-CoV-2 virus that causes the COVID-19 disease[7,8]. They examined 48 European countries and territories, including the Monaco and Andorra principalities and Vatican City, and the 30 most afflicted countries globally, at the time of their study[7,8]. They reported that simple cross-sectional regressions, using country populations, were able to predict quite accurately both the total number of cases and deaths, which cast doubt on measures aimed at controlling the disease via lockdowns.

Nevertheless, the policies aimed at combatting pandemics have implications on numerous different fronts, apart from the direct economic impact of containment policies there are social, institutional, and cultural effects,[9].

Tiganasu et al. (2022), suggest that socio-demographic factors are important in explaining the different incidence rates of COVID-19 in European countries[10]. Sharma et al., (2021) analyse the effects of use non-pharmaceutical interventions (NPIs) by European governments to control resurging waves of COVID-19, and report that the combined effect of all NPIs was smaller in the second wave than in the first[11].

Gostin et al., (2023) highlight the fact that response to the pandemic caused the failure of many states to live up to their human rights obligations[4]. They note that the pandemic began with Wuhan officials in China suppressing information, silencing whistleblowers, and violating the freedom of expression and the right to health. Subsequently they suggest that COVID-19's effects have been profoundly unequal, both nationally and globally.

Fuss et al., (2023) draw attention to evidence of a different behaviour of Omicron waves in terms of wave dynamics, and thereby confirm that the Omicron variant is not only genetically different but even more so in terms of epidemiological dynamics[12].

Maggazinno et al., (2022) use a machine learning approach to study the efficacy of COVID-19 vaccination effectiveness, in a sample based on 192 countries, for the period March to May 2021, and report that the vaccination campaign significantly reduced the negative effects of the COVID-19 pandemic, with a sharp decrease in fatality rates[13].

Matveeva and Shabalina (2023) use data for 29 countries to evaluate the effect of vaccination/booster administration dynamics on the reduction of excess mortality during COVID-19 infection waves in European countries[14]. They report that the "faster" countries, as opposed to the "slower" ones, did better in protecting their residents from mortality during all periods of the SARSCoV-2 pandemic and even before vaccination. They analysed different time periods in the pandemic roughly corresponding to different strains of the virus and noted that vaccine protection peaked in the Delta wave but became weaker in the Omicron wave. They also suggest that the excess mortality during the COVID-19 pandemic correlated not only with a county's vaccination rate, but also with its per capita GDP. The latter parameter likely reflects and is related to the quality of healthcare in the country, the availability of mass COVID-19 testing, and funding for other pandemic mitigation strategies.

Meyer (2023) analyses the impact of COVID-19 vaccines on all-cause mortality in the EU in 2021 using a machine learning approach[15]. He reports that the benefit-risk balance for the 0-44 years old is not in favor of the vaccines. Nafilyan et. al. (2023) show that in the 12-29 year age group, there is no significant increase in cardiac or all-cause mortality in the 12 weeks following COVID-19 vaccination compared to more than 12 weeks after any dose[16].

Ale et. al. (2021), discuss the nature of the risk profiles of COVID vaccine recipients and suggest that it is likely to be much more nuanced and therefore likely to vary greatly according to individual circumstances, than suggested in the information promoted by policy makers during the pandemic[17].

In this brief review of some of the relevant literature I draw on some of the previous work that is relevant to the ground explored in the current paper. The central issue is the linkage between vaccination rates in response to the COVID-19 pandemic and excess death rates. The results seem to vary according to which stage during the pandemic that the study was undertaken. Many are favourable to the vaccination strategy but Meyer (2021), casts doubt about its cost\benefit ratio in younger age categories[15].

This paper takes a country level view of these issues employing aggregate data for OECD countries and relies on very broad indices to capture the relevant effects. The influence of different forms of virus and the recent Omicron variants is ignored in that the measures used are summary ones reflecting the country specific totals at a particular point in time: namely the end of 2022 beginning of 2023. These limitations must be borne in mind when considering the results that follow.

3. Materials and Methods

The original data used in Allen (2023) was downloaded from https://www.worldometers.info/coronavirus/ (Accessed 17 January 17 2023) [1]. The data series included OECD countries and involved aggregate series per country such as population, total cases, new cases, total deaths, new deaths, total recovered, new recovered, active cases, serious critical cases, total deaths per million population, total tests and tests per million population.

The Oxford Stringency Index was downloaded from Github. (https://github.com/OxCGRT, accessed on 22 January 2023. The value of the index for each country is reported daily until the end of 2022. To achieve a summary measure, I cumulated the daily values for each country to achieve an overall score for that country. The assumption was that a higher score involves more stringent policies up to that point in time, over a longer period. The median value of the result for this country index was 46793, with a minimum score of 32 and a maximum of 69124.

The GHS index was downloaded directly from their website. (https://www.ghsindex.org, accessed 22 January 2023). The median value for the GHS index was 36.4, with a minimum of 16 and a maximum of 75.9.

The Indices of Trust were downloaded from the 'Ourworldindata' website, https://ourworldindata.org/trust and from the OECD, as accessed on 22 January 2023. The Trust index is described in Algan and Cahan (2010) and reflects measures taken in (2014)[18]. The median value of the Trust Index was 43.670 with a minimum value of 21.58 and a maximum of 83.78. The PTI index is a measure of personal trust taken from OECD data sources. It had a median value of 0.32, with a minimum value of 0.11 and a maximum of 0.68.

The data on COVID vaccine booster doses was downloaded from the ourworldindata.org website on 23 August 2023. (See: https://ourworldindata.org/grapher/cumulative-covid-vaccine-booster-doses). The measure is defined as the total number of vaccine booster doses administered, divided by the total population of the country (CB). Booster doses are doses administered beyond those prescribed by the original vaccination protocol.

One of the observed phenomena across the world since the pandemic is a pronounced excess death rate across all age groups. This study will use OECD weekly data on excess deaths sourced from OECD statistics (https://stats.oecd.org/index.aspx?queryid=104676#), as accessed on 23 August 2023.

The analysis will use OLS in cross-section. One of the problems encountered is that some countries have stopped collecting official statistics at the end of 2022. Most of the data will reflect the position at the end of 2022 or the beginning of 2023. The measure of cumulative booster vaccine doses (CB) is a measure taken at this point in time. The excess deaths (EXED), in the preliminary analysis in this proposal, reflects the recorded statistics in OECD countries in the first week of 2023. This will be augmented by a metric reflecting the average excess deaths over the first 3 months of 2023 (AVEXED), given that this data is available.

Figure 1 suggests a number of potential causal links in the data to be used in the analysis. The data for each country varies in quality and suffers from several inherent drawbacks. There is potential confusion between deaths from covid and deaths with covid. The red arrows in the diagram map out potential links between the variables used in the analysis. The contraction of covid could weaken a person's immune system and lead to subsequent death from other causes. 'However, this might be revealed in a subsequent statistical association between case rates and excess deaths. A counter argument would suggest that contracting covid could enhance natural immunity and lead to subsequent greater resilience against covid.

Descriptive statistics relating to these measures are provided in Table 1.

3a. Econometric methods

The analysis involved several ordinary least squares regressions (OLS). For example, the number of excess death cases EXEDi, for each country i, was regressed on the total sum of cumulated booster doses of that country CBi, as shown in Eq. (1)

$$EXED_i = a + bCB_i + e_i . \qquad (1)$$

This was repeated with average excess deaths for the first 3 months in 2023, in each country $AVEXED_i$ as the dependent variable.

$$AVEXED_i = a + bCB_i + e_i . \qquad (2)$$

This establishes a simple benchmark, which countries had more than average excess deaths cases, in the initial week, or in the first three months of 2023, per total of cumulative vaccine booster doses, and which had less.

The above relationships can also be explored using logarithms of the variables. This has the advantage of highlighting proportionate responses, but the disadvantage that it is not possible to take the logarithm of negative numbers, so some observations may be lost.

To explore the relationship between the experience of excess deaths and previous infections, the regression below can be estimated. This should shed some light on whether previous infections provide natural immunity, which would be indicated by a significant negative slope coefficient, or weaken the immune system, and lead to more excess deaths, which would be indicated by a significant positive slope coefficient.

$$AVEXED_i = a + bTOTALRECOVERED_i + e_{i.} \qquad (3)$$

This relationship can also be explored in logarithmic format. Allen (2023) reported that the use of logarithmic formats in relationship to COVID-19 analyses, appeared to provide superior results[1].

The interpretation of logarithmic regressions is slightly different from standard regressions. The interpretation of the above relationship in equation (1) is given as an expected percentage change in $EXED_i$ when CB_i increases by one percent. Such relationships, where both $EXED_i$ and CB_i are log-transformed, are commonly referred to as elasticities in economics, and the coefficient of log CB_i is referred to as an elasticity. In terms of the effects of changes in CB_i on $EXED_i$:

- multiplying CB_i by e will multiply expected value of $EXED_i$ by e^b.
- to obtain the proportional change in $EXED_i$ associated with a p percent increase in CB_i, calculate a = log ([100 + p]/100) and take e^{ab}.

Figure 1 shows how there are a number of potential linkages between the variables used in the analysis. It may be the case that excess deaths are linked to the severity of restrictions such as lockdowns, which may have prevented normal medical screening for the presence of diseases taking place during the pandemic. This would then lead to excess morbidity subsequently being observed, if earlier diagnosis and treatment might have improved medical outcomes. This can be explored by the use of bivariate regressions. The analysis can then be repeated using the various indices as benchmarks, if I_i represents the Index for country i, excess deaths can be regressed on Index I_i, to explore whether the index has any explanatory power.

$$EXED_i = a + bSTR_i + e_i \quad (4)$$

Equation (4) explores the impact of the Oxford University Stringency Index, whilst equation (5) examines the influence of the GHS Index.

$$EXED_i = a + bGHS_i + e_i \quad (5)$$

The relationship between average excess deaths and the various other indices can be explored in a similar fashion. Measures of trust and gdp/capita can similarly be analysed.

In addition, the regressions can be run in multivariate format to see if the Indices have any explanatory power when included in the original regressions shown above. If there is a dilemma about which explanatory variables to include one way of choosing which to include is to run a lasso regression.

The adaptive lasso regression uses different penalties (weights) for different regressors when running a lasso regression. Under certain conditions as applied to those weights, the results will have the so-called Oracle property, see Zhou (2006) as opposed to the standard lasso approach[19].

Zou (2006) derives a necessary condition for the lasso variable selection to be consistent [19]. His version of the lasso, the adaptive lasso employs adaptive weights that are used for penalizing different coefficients in the λ_1 penalty. He demonstrates that the adaptive lasso enjoys oracle properties; namely, that it performs as well as if the true underlying model were given in advance.Zou (2006) suggests that $\mathbf{y} = (y_1,\ldots,y_n)^T$ is the response vector and $\mathbf{x}_j = (x_{1j},\ldots,x_{nj})^T$, $j = 1,\ldots,p$, are the linearly independent predictors [19]. He lets $\mathbf{X} = [\mathbf{x}_1,\ldots,\mathbf{x}_p]$ be the predictor matrix. He assumes that $E[y|\mathbf{x}] = \beta^*_1 x_1 + \cdots + \beta^*_p x_p$. The data is assumed to be centred so the intercept is not included in the regression equation. He lets $A = \{j : \beta_j^* \neq 0\}$ and then assumes that $|A| = p_0 < p$. This implies that the true model depends only on a subset of the predictors.

If we denote by $\hat{\beta}$ *(Δ)* the coefficient estimator produced by a fitting procedure *Δ*. Then the arguments of Fan and Li (2001) [20], can be adopted and *Δ* can be termed as being an *oracle* procedure if $\hat{\beta}$ *(Δ)* (asymptotically) has the following oracle properties:

- Identifies the right subset model, $\{j : \hat{\beta}_j \neq 0\} = A$
- Has the optimal estimation rate, $\sqrt{n}\,\hat{\beta}((\Delta)A - \boldsymbol{\beta}^*A) \to_d N(0, \boldsymbol{\Sigma}^*)$, where $\boldsymbol{\Sigma}^*$ is the covariance matrix knowing the true subset model.

The lasso is a regularization technique for simultaneous estimation and variable selection Tibshirani (1996) [21]. The lasso estimates are defined as:

$$\hat{\beta}(lasso) = \underset{\beta}{\arg\min} \left\| y - \sum_{j=1}^{p} x_j \beta_j \right\|^2 + \lambda \sum_{j=1}^{p} |\beta_j| ,$$

where λ is a nonnegative regularization parameter. The second term in the expression above is the so-called "ℓ_1 penalty," which is crucial for the success of the lasso. The lasso continuously shrinks the coefficients toward 0 as λ increases, and some coefficients are shrunk to exact 0 if λ is sufficiently large.

Zou proposes the adaptive lasso, in which adaptive weights are used for penalizing different coefficients in the ℓ_1 penalty and he demonstrates that the adaptive lasso enjoys the oracle properties [19]. He employs $\hat{\beta}$ *(ols)* to construct the adaptive weights in the adaptive lasso; and suggests that the computation procedure involves the employment of the LARS algorithm (Efron et al. 2004)[22].

This version of the adaptive lasso technique using a GRETL function package containing code submitted by Schreiber (2023), was used to select variables for final inclusion in the multivariate regressions[23].

4. Results

The results of the regression analysis are shown in Table 2. The first row in Table 2 reports the results of the regression of excess deaths, in the first week of 2023, by country, on country cumulated booster vaccination totals. The slope coefficient is positive, significant, and the overall regression is also significant at the one per cent level. The Adjusted R-Squared is a massive 79 percent. This suggests that on average, almost eighty percent of the variation in the total number of excess deaths per country, in the first week of 2023, can be explained by variations in the number of booster vaccinations per country. Figure 2 shows the fit of this regression line. The USA, Germany, the UK, Poland, the Netherlands, Austria and Hungary, plot above the line, whilst France, Columbia, Spain and Italy, plot below it, all having fared better than average in their experience of excess deaths in the first week of 2023.

The second row reports the results of the regression of the logarithm of excess deaths in the first week of 2023, by country, on the logarithm of country cumulative booster totals. One complication is that a few observations are dropped because it is not possible to take the logarithm of negative numbers. This formulation, shows proportionate responses, given its in logarithmic form, and is also significant at the one per cent level, for both the slope coefficient, which is now 0.75, and regression equation, which has an F statistic of 82.68, whilst the Adjusted R-square reduces to 74 per cent.

In terms of elasticities, this result suggests that a 1 per cent increase in the uptake of excess booster vaccines in OECD countries will lead to a 7.5 per cent increase in excess deaths.

Figure 3 shows the fit of this regression line, and it suggests that in terms of the average relationship between the number of excess deaths in the first week of 2023 and cumulative booster doses per country, the USA, the UK, Germany, France, Poland, Austria, the Netherlands, Czechia, Lithuania, Slovakia and Latvia, all plot above the line. in the region of heavily populated countries. By contrast, Australia, Canada, Chile, Spain, Columbia, New Zealand, Israel, Sweden, Switzerland, Belgium, Greece, Norway, and Iceland, plot below the line.

The analysis is then repeated using the average number of excess deaths in the first three months of 2023 as the dependent variable. The results of this regression are shown in the third row of Table 2. The slope coefficient is positive, significant at the 1 percent level, the Adjusted R square is 0.75, while the F statistic has a value of 92.25 and is significant at the 1 percent level.

The fourth row of Table 2 reports this regression relationship in logarithmic format. The slope coefficient is now 1.15 and significant at the 1 per cent level. The fact that the value is above 1 suggests a greater than proportionate increase in average excess deaths to an increase in booster vaccinations. The F statistic for the regression is also significant at the 1 per cent level. The elasticity is roughly a 1.15 per cent increase in average excess deaths for a 1 per cent increase in excess booster doses.

The adjusted R-squares to these regression formulations vary between 0.79 and 0.69. This suggests that around 70 per cent or more of excess deaths experienced in OECD countries at the beginning of 2023 can be attributed to variations in cumulated booster vaccinations.

Figure 4 presents a graph of this regression relationship. The USA, Germany, Australia, Chile, the Netherlands, New Zealand, Greece, Finland, Denmark, Israel, Lithuania and Iceland, all plot above the regression line. This suggests that these countries have above average excess deaths, at least in the context of this data set. Spain, France, Canada, Norway, Portugal, Slovenia, and Luxembourg, plot below the line, implying the reverse.

Spain faired relatively poorly in terms of death rate/million population during the pandemic with a figure of 610 deaths per million, this was similar to the figure for the UK which was 683 deaths per million, yet the UK sits above the line in Figure 4, whilst Spain is below it. The analysis does not recognize the various stages in the pandemic, or the fact that subsequent variants of the virus, such as omicron, were less severe than the original. It may be the case that infection confers natural immunity and subsequently reduces the number of excess deaths, or the reverse might apply, and infection could conceivably weaken the immune system leading to more subsequent excess deaths. This can be explored by examining the relationship between recovered cases and subsequent excess deaths rates across this OECD country sample.

Row 4 in Table 2 reports the results of estimating this regression relationship. The slope coefficient is positive, has a value of 0.0007 which is significant at the 10 per cent level, the Adjusted R-square is only 0.082, and the regression itself is also significant at the 10 per cent level.

The next row in Table 2 reports the results of running the same regression in logarithmic format. The slope coefficient is now a positive 0.32 which is significant at the 1 per cent level. The Adjusted R-square is now 0.27, and the F statistic for the regression, with a value of 9.68, is also significant at the 1 per cent level. Thus, approximately a quarter of excess deaths, across OECD countries, appear to be related to having previously suffered from COVID. This supports the hypothesis that contracting COVID serves to weaken the immune system rather than conferring benefits of enhanced immunity, if the benchmark adopted is the number of subsequent excess deaths.

Figure 5 presents a graph of the logarithmic relationship between excess deaths and the total number of recovered persons. The USA, Germany, Poland and France plot well above the line, whilst Switzerland, Slovakia, Israel, Luxembourg, Estonia and Iceland, plot well below it.

The regression is then repeated using the average number of excess deaths in the first 3 months of 2023 and the results are shown in row 7 of Table 2. The slope coefficient of 0.000436537 is significant at the 5 per cent level, the Adjusted R-square is 0.16 and the F statistic is significant at the 5 per cent level. The next row in Table 2 shows the results of the same regression in logarithmic format.

This is a stronger regression results with a slope coefficient on the logarithm of the total number of recovered persons with a value of 0.658006, which is significant at the 1 per cent level, the Adjusted R-square increases to 0.32, and the F statistic of 9.055 is also significant at the 1 per cent level.

This result suggests that previous exposure to COVID-19 increases the likelihood of greater experience of average excess deaths across this sample of OECD countries, but the regression only explains about 30 percent of the average of excess deaths and the response to a 1 per cent increase in the level of previous exposure to COVID-19 has an elasticity of about 0.65 of a per cent. This result contrasts with a much greater response in the experience of average excess deaths to a 1 per cent increase in excess booster vaccinations.

A plot of this regression is shown in Figure 6. What is notable from the graph is that both Australia and New Zealand plot well above the regression line, as do Germany and the USA, yet Australia and New Zealand fared relatively well in terms of COVID-19 fatalities, and yet they have not done well in relation to the number of excess deaths that they have experienced. New Zealand had 4 deaths per million during the pandemic, the lowest level, followed by Slovakia with 5, S. Korea 6, Japan 8, whilst Australia with 10 deaths per million was the next. Greece had 20 and Lithuania 20 deaths per million population. The USA and Germany had relatively higher numbers at 492 and 110 deaths per million population.

If excess covid booster shots play a major role in explaining excess deaths it is worth exploring whether OECD countries that had greater emphasis on stringent COVID-19 policies had a greater tendency towards requiring their citizens to have more booster vaccinations? Preliminary exploratory regressions, revealed once again, that a logarithmic format worked well.

Row 9 of Table 2 reports the results of regressing the logarithm of CB on the logarithm of the Stringency Index. The slope coefficient of this regression has a value of 7.30965 significant at the 1 per cent level, the Adjusted R-square is 0.40 and F statistic of 25.84 is significant at the 1 per cent level. Thus, the country level of stringency has a significant positive effect on the adoption of excess booster vaccinations.

The next row of Table 2 shows the result of the substitution of the logarithm of the GHS index for STR. This regression has a similar but less powerful result. The slope coefficient is 4.25248, significant at the 5 per cent level, the Adjusted R-square drops to 0.09, and the F statistics with a value of 4.72, is also significant at the 5 per cent level.

Similar regressions using the logarithm of CB as the dependent variable and the logarithms of TRUST, PTI and GDP/CAP were also undertaken, but all proved to be insignificant. It seems to be the case that the stringency of OECD country policies towards COVID-19 has been associated with the population of those countries having more excess booster doses and subsequently more excess deaths.

This raises the issue of the relationship between excess deaths and the stringency of government policies. A number of different regression specifications were explored and the regression of the logarithm of excess deaths on the logarithm of the Stringency Index seemed to outperform the other specifications, in terms of the Adjusted R-square. This regression is reported in row 11 of Table 2. The slope coefficient of 5.11176 is significant at the 1 percent level, the Adjusted R-square is 0.28 and the F statistic of 12.15 is significant at the 1 per cent level.

A plot of this regression relationship is shown in Figure 7. It seems that in terms of the relative degree of stringency of the policies adopted by OECD countries, the USA, the UK, Germany, France and Poland, had more excess deaths than would be expected, whilst Greece, Spain, Luxembourg and Iceland, had relatively fewer.

A similar regression was estimated using the logarithm of average excess deaths as the dependent variable and is reported in row 12 of Table 2. The slope coefficient is 7.07 which is significant at the 5 per cent level. The Adjusted R-square is 20 per cent and the F statistic of 5.91 is also significant at the 5 per cent level.

In summary, it seems that in terms of Adjusted R squares, excess deaths and average excess deaths are best explained by the extent of cumulative booster doses administered in a given OECD country. However, the adoption of these policies is also explained by the degree of stringency in the individual OECD country and excess deaths are also positively related to the number of recovered cases of COVID-19. These relationships can be further explored by the application of multivariate regression analysis.

Table 3 reports the results on an OLS regression of the logarithm of excess deaths in the first week of 2023 lEXED, on the logarithm of excess booster vaccinations, lCB, plus the logarithms of two measures of stringency lSTR and lGHS, the logarithms of two measures of trust, lPTI and lTRUST, the logarithm of GDP per capita, lGDPCAP, and the logarithm of the total number of recovered lTOTALRecovered. (Note: The econometrics software used for the analysis, GRETL, adds an '_' when taking the logarithm of a series, I have ignored this convention when reporting the variables).

In this regression only the slope coefficient on excess booster vaccinations is significant with a value of 0.81, significant at the 1 per cent level, and the regression has an Adjusted R-square of 0.81 and an F statistic of 15.77, which is significant at the 1 per cent level.

To reduce the number of explanatory variables and adaptive lasso analysis was run on the set of explanatory variables and the result suggested that only lCB, lGHS and lTrust should be included in the regression. Table 4 reports the results of this regression. The slope coefficient on the lCB has a value of 0.670506 which is significant at the 1 per cent level. The coefficient on lGHS is 2.15359 significant at the ten per cent level, whilst the coefficient on lTrust l is insignificant. The regression has an Adjusted R-square of 0.76 and an F statistic of 30.58 and is significant at the one per cent level.

This analysis is repeated with lAVEXED as the dependent variable. Table 5 reports the results of a multiple regression which includes the logarithm of excess booster vaccinations, lCB, plus the logarithms of two measures of stringency lSTR and lGHS, the logarithms of two measures of trust, lPTI and lTRUST, the logarithm of GDP per capita, lGDPCAP, and the logarithm of the total number of recovered lTOTALRecovered as the explanatory variables. The coefficient on lCB is 1.43153, which is significant at the one per cent level, the coefficient on lPTI is 2.86526 significant at the five per cent level, whilst the coefficient on lTRUST is −3.17156 which is also significant at the five per cent level. It is notable that there are two different signs on the two trust indices. The regression has an Adjusted R-square of 0.80 and a F statistic of 10.97 which is significant at the one per cent level.

An adaptive lasso analysis of this regression suggests the retention of lCB lPTI lTRUST and lGDPCAP as the explanatory variables. Table 6 reports the results of this regression. The slope coefficient on lCB is 0.980819 which is significant at the one per cent level. The coefficients on the two trust indices lPTI and lTRUST are 2.73217 and −2.50094 respectively, with the former significant at the one per cent and latter five per cent levels. The influence of lGDPCAP is insignificant. On balance the two trust indices have a small positive effect. The Adjusted R-square of this regression is a massive 82 per cent. The F statistic is 23.60 which is significant at the one per cent level.

Figure 8 provides a plot of this regression relationship. The USA, the UK, Germany, the Netherlands, Greece, New Zealand, Lithuania, Israel, Portugal and Iceland, all plot above the regression line, indicating they have greater than expected excess deaths when the regression line is used as a benchmark. By contrast, Luxembourg, Slovenia, Canada and Spain, all plot well below the line.

Finally, Figure 9 provides a plot of the actual logarithm of average excess deaths, LAVEXED against the fitted values for this variable graphed against the value of the logarithm of excess booster vaccines. This graph shows that the predicted values are a good fit, which is expected given the Adjusted R-square is over 80 per cent, but there is also a clear positive relationship with the value of the logarithm of the excess booster vaccine per OECD country lCB_i.

5. Discussion

This paper features an analysis of OECD country level data generated by the COVID-19 pandemic as revealed in data related to booster vaccinations, excess deaths, populations, infections, recovered cases, for a sample of 38 countries, plus measures of their policy responsiveness and relative preparedness. The paper uses OECD weekly data on excess deaths. The data on COVID-19 vaccine boosters administered was obtained from ourworldindata.org, the assessment includes measures of GDP per capita, and indices of country specific trust levels, the cumulative data set is taken from the Worldometer data source. The GHS Index and Oxford Stringency Index are used as policy benchmarks. Other indicators used include GDP/capita, Trust, and Personal Trust Indices from the OECD.

Univariate and multivariate regression analyses reveal that there is a major association between COVID booster vaccinations and excess deaths across the sample of 38 OECD countries in the cross-sectional regression analyses undertaken. The regressions perform better in a logarithmic format but the drawback of this form of analysis is the loss of observations that feature negative numbers. The data is aggregated, and the author is aware of the variability and lack of accuracy in some of the national data sets. The problems are compounded by the fact that many of the series ceased to be collected at the end of 2022 when the pandemic was deemed to be 'over'.

Nevertheless, a clear picture emerges from the regression analysis. This suggests a very high level of association between booster vaccinations and excess deaths. There is a positive significant association between the number of recovered cases per OECD country and subsequent excess deaths, but the effect is much greater in the case of booster vaccinations. The number of booster vaccinations undertaken is significantly associated with the degree of stringency of the COVID policies of individual OECD countries. In turn, excess deaths and average excess deaths are linked to OECD country stringency policies.

However, as Figure 1 demonstrates, more stringent policies are likely to lead to more emphasis and promotion of booster vaccinations. In univariate regressions these other variables have less than half the explanatory power of COVID booster vaccinations.

If these variables are added to the list of explanatory variables to explain excess deaths, most are insignificant and booster vaccinations dominate. An adaptive lasso technique was used to screen the set of potential explanatory variables. This suggested that the GHS Index and TRUST in logarithmic form be included in the explanatory variables used to explain the logarithm of excess deaths per OECD country across the first week of 2023. The results were disappointing in that the GHS index was significant at the 10 per cent level and TRUST was insignificant.

The results in the regression featuring the logarithm of average excess deaths in OECD countries across the first three months of 2023 were more successful and the adaptive lasso technique suggested the inclusion of the logarithms of PTI, Trust and GDP per capita, in addition to booster vaccinations as explanatory variables. This regression was more successful, in that apart from booster vaccinations, PTI was significant at the one per cent level, and TRUST at the five per cent level, though GDP per capita was insignificant. It was notable that the two trust indices had opposite signs. The Adjusted R-square of this regression was a remarkable eighty-two per cent. It seems that trust in government plays a role in persuading individuals to take up booster vaccinations.

6. Conclusion

In summary, the clear impression across the various regression analyses is that COVID booster vaccinations, have by far the greatest explanatory power in the explanation of excess deaths across this sample of OECD countries. Thus, there does appear to evidence of a high degree of association in this OECD dataset that links excess deaths to the take up of booster vaccinations. These results are similar in part to Meyer (2021)[15].

This has recently become a topic of considerable interest in that the British MP, Andrew Bridgen, in an Adjournment Debate in the Houses of Parliament on October 20th 2023, became the first MP to officially raise this matter as an important public interest topic. The topic merits further exploration.

Conflict of Interest Statement:

The author is not aware of any conflicts of interest.

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Table1. Descriptive Statistics Base Series

Variable	Mean	minimum	maximum	St.Dev.	C.V.
Population	3.6076e+007	3.4147e+005	3.3120e+008	5.9788e+007	1.6573
Total Cases	3.7404e+005	1275.0	5.0322e+006	1.0642e+006	2.8452
Total Deaths	11945	10.000	1.6280e+005	28302	2.3693
Total Recovered	2.9941e+005	1070.0	4.3478e+006	8.6322e+005	2.8830
Tot Cases 1Mpop	33719	283.00	6.3406e+005	1.2837e+005	3.8071
Deaths 1Mpop	332.42	4.0	3386.0	605.31	1.8209
Total Tests	4.5446e+006	96110	6.3140e+007	1.0843e+007	2.3859
Tests 1Mpop	2.3689e+005	7425.0	2.6562e+006	4.7842e+005	2.0196
GDP CAP	44221	6104.1	1.3359e+005	27981	0.63275
TRUST	47.803	21.58	83.780	16.564	0.34651
PTI	0.34297	0.11	0.68	0.14751	0.43010
STR	45424	32879	58151	6546.2	0.14411
GHS	58.882	40.80	75.90	7.5651	0.12848
CB	2.0512e+007	2.4961e+005	1.3306e+008	2.7837e+007	1.3571
EXED	879.69	-149.00	8701.2	1871.3	2.1272
AVEXED	280.10	-241.12	4959.1	923.47	3.2969

Table 2

OECD Regression Results

Regression equation	Slope Coefficient	Adjusted R-Square	F Statistic
$EXED_i = a + bCB_i + e_i$	0.000063***	0. 7923	119.22***
$lEXED_i = a + blCB_i + e_i$	0.7512***	0.7447	82.68***
$AVEXED_i = a + bCB_i + e_i$.	0.00003***	0.75	92.25***
$lAVEXED_i = a + blCB_i + e_i$	1.1486***	0.69	45.35***
$EXED_i = a + bTOTALRECOVERED_i + e_i$	0.0007*	0.082	3.42*
$lEXED_i = a + blTOTALRECOVERED_i + e_i$	0.3220***	0.27	9.68***
$AVEXED_i = a + bTOTALRECOVERED_i$	0.000436537**	0.16	5.98**
$lAVEXED_i = a + blTOTALRECOVERED_i + e_i$	0.658006***	0.32	9.055***
$lCB_i = a + blSTR_i + e_i$	7.30965***	0.40	12.15***
$lCB_i = a + bGHS_i + e_i$	4.25248**	0.09	4.73**
$lEXED_i = a + blSTR_i + e_i$	5.11176***	0.28	12.15***
$lAVEXED_i = a + blSTR_i + e_i$	7.07375**	0.20	5.91**

Note: ***,**,* Indicate significance at the 1, 5, and 10 per cent levels respectively.

Table 3: OECD Multivariate Regression Results Dependent Variable $lEXED_i$

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−2.26984	13.9670	−0.1625	0.8728	
lCB	0.813119	0.148570	5.473	<0.0001	***
lSTR	−1.41367	1.38668	−1.019	0.3223	
lGHS	2.01999	1.33875	1.509	0.1497	
lPTI	−0.546447	0.686214	−0.7963	0.4368	
lTRUST	−0.875046	0.636603	−1.375	0.1871	
lGDPCAP	0.480840	0.381356	1.261	0.2244	
lTotalRecovered	−0.00958850	0.0691090	−0.1387	0.8913	

Mean dependent var	5.674199	S.D. dependent var	1.446427
Sum squared resid	6.700086	S.E. of regression	0.627792
R-squared	0.866563	Adjusted R-squared	0.811618
F(7, 17)	15.77157	P-value(F)	2.69e-06
Log-likelihood	−19.01402	Akaike criterion	54.02804
Schwarz criterion	63.77905	Hannan-Quinn	56.73256

Note: ***,**,* Indicate significance at the 1, 5, and 10 per cent levels respectively.

Table 4: OECD Multivariate Regression Results Dependent Variable $lEXED_i$

OLS, using observations 1-38 (n = 29)
Missing or incomplete observations dropped: 9
Dependent variable: lEXED

	Coefficient	Std. Error	t-ratio	p-value	
const	−11.8320	4.51192	−2.622	0.0147	**
lCB	0.670506	0.0918080	7.303	<0.0001	***
lGHS	2.15359	1.24964	1.723	0.0972	*
lTRUST	−0.434209	0.348707	−1.245	0.2246	

Mean dependent var	5.776005	S.D. dependent var	1.426684
Sum squared resid	12.20358	S.E. of regression	0.698672
R-squared	0.785872	Adjusted R-squared	0.760176
F(3, 25)	30.58418	P-value(F)	1.58e-08
Log-likelihood	−28.59850	Akaike criterion	65.19700
Schwarz criterion	70.66618	Hannan-Quinn	66.90988

*Note: ***,**,*, Indicate significance at the 1, 5, and 10 per cent levels respectively.*

Table 5: OECD Multivariate Regression Results Dependent Variable $lAVEXED_i$

OLS, using observations 1-38 (n = 18)
Missing or incomplete observations dropped: 20
Dependent variable: lAVEXED

	Coefficient	Std. Error	t-ratio	p-value
const	38.1309	28.8310	1.323	0.2154
lCB	1.43153	0.400574	3.574	0.0051***
lSTR	−1.90076	2.62679	−0.7236	0.4859
lGHS	−2.98813	2.54476	−1.174	0.2675
lPTI	2.86526	1.11409	2.572	0.0278 **
lTRUST	−3.17156	1.36487	−2.324	0.0425 **
lGDPCAP	−0.58395	0.936376	−0.6236	0.5468
lTotal Recovered	−0.195205	0.260788	−0.7485	0.4714

Mean dependent var	4.096230	S.D. dependent var	2.345109
Sum squared resid	10.80943	S.E. of regression	1.039684
R-squared	0.884381	Adjusted R-squared	0.803448
F(7, 10)	10.92732	P-value(F)	0.000565
Log-likelihood	−20.95132	Akaike criterion	57.90263
Schwarz criterion	65.02560	Hannan-Quinn	58.88479

*Note: ***,**,*, Indicate significance at the 1, 5, and 10 per cent levels respectively.*

Table 6: OECD Multivariate Regression Results Dependent Variable $lAVEXED_i$

OLS, using observations 1-38 (n = 21)
Missing or incomplete observations dropped: 17
Dependent variable: lAVEXED

	Coefficient	Std. Error	t-ratio	p-value	
const	9.61742	7.44330	1.292	0.2147	
lCB	0.980819	0.138248	7.095	<0.0001	***
lPTI	2.73217	0.732916	3.728	0.0018	***
lTRUST	−2.50094	1.12790	−2.217	0.0414	**
lGDPCAP	−0.749239	0.713074	−1.051	0.3090	

Mean dependent var	4.389222	S.D. dependent var	2.308971
Sum squared resid	15.45260	S.E. of regression	0.982745
R-squared	0.855078	Adjusted R-squared	0.818847
F(4, 16)	23.60104	P-value(F)	1.53e-06
Log-likelihood	−26.57689	Akaike criterion	63.15377
Schwarz criterion	68.37638	Hannan-Quinn	64.28721

Note: ***,**,*, Indicate significance at the 1, 5, and 10 per cent levels respectively.

Figure 1: Schema of potential relationships between variables used in the analysis

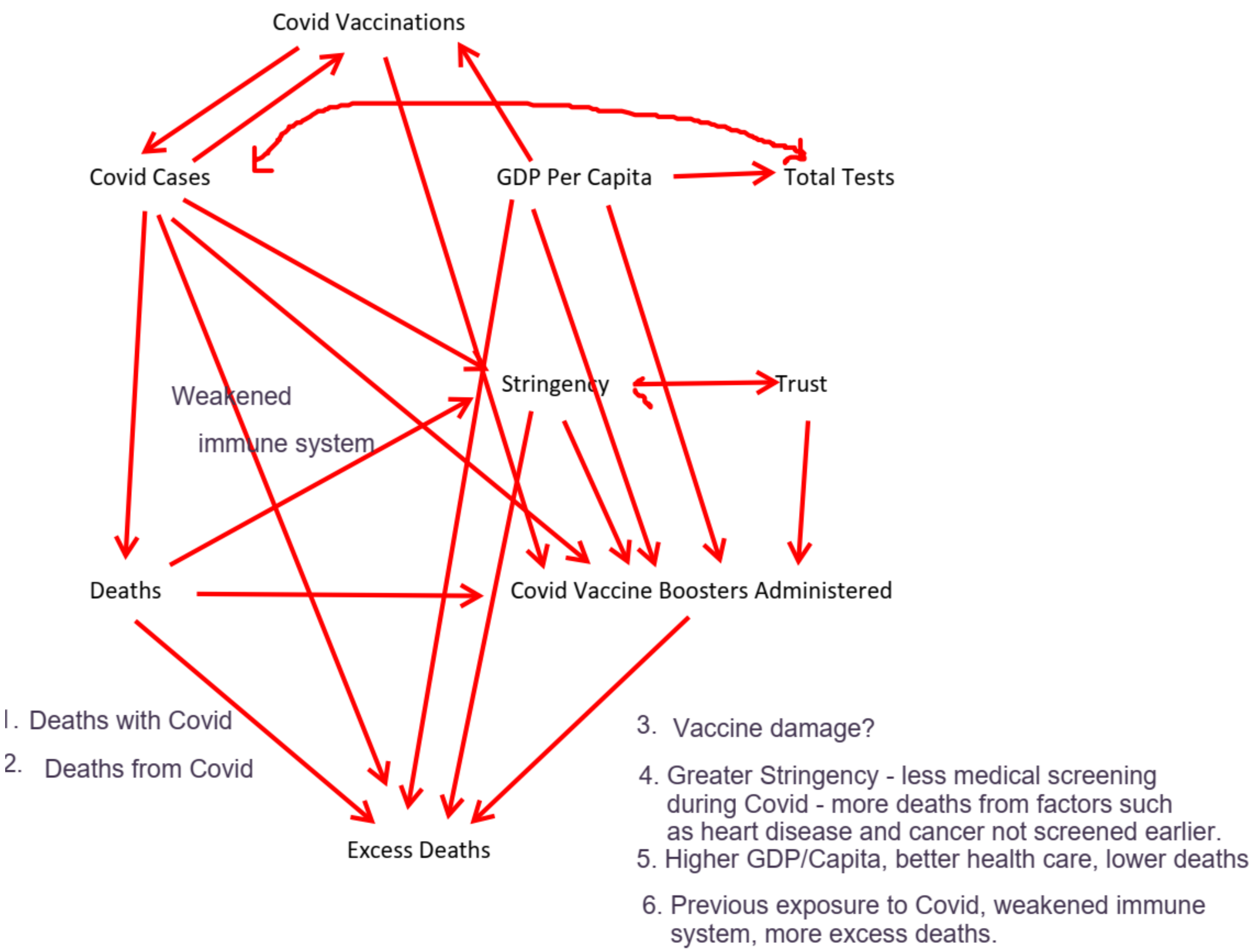

Figure 2: Regression $EXED_i = a + bCB_i + e_i$

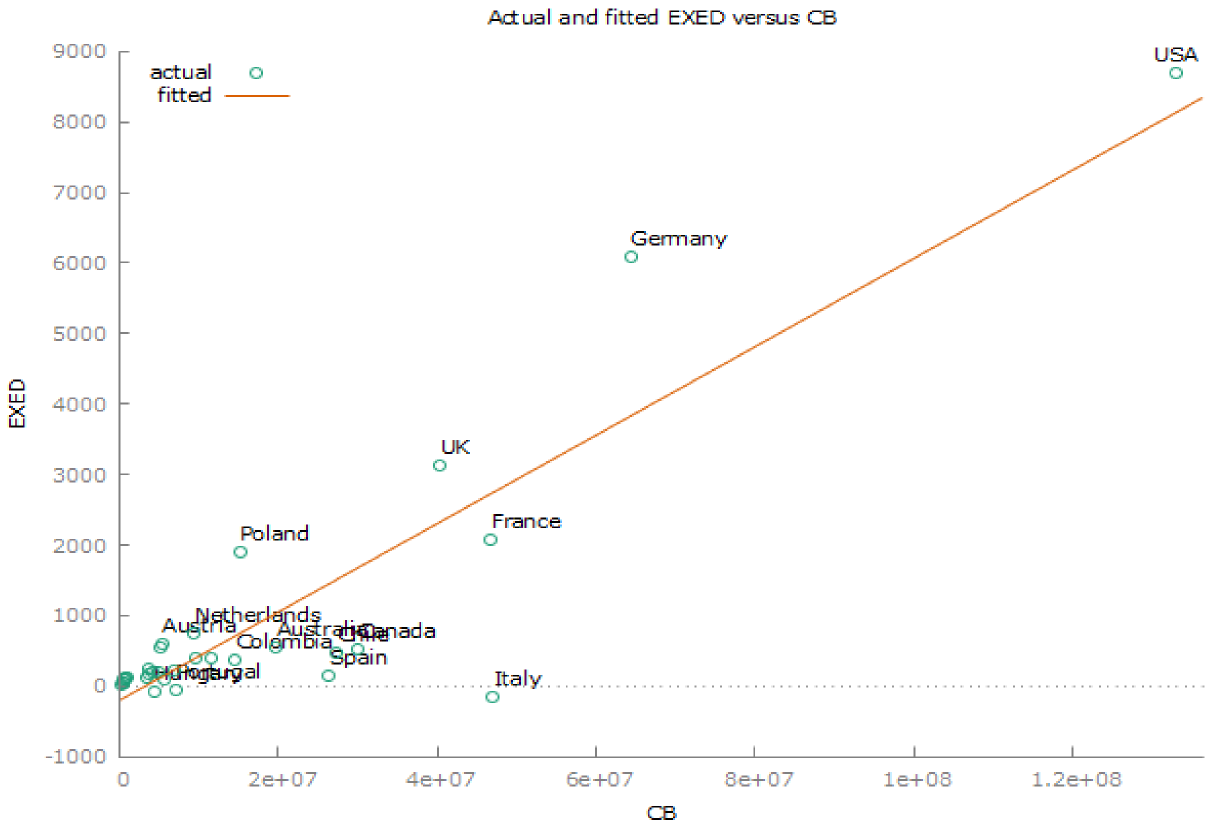

Figure 3: Regression $lEXED_i = a + blCB_i + e_i$

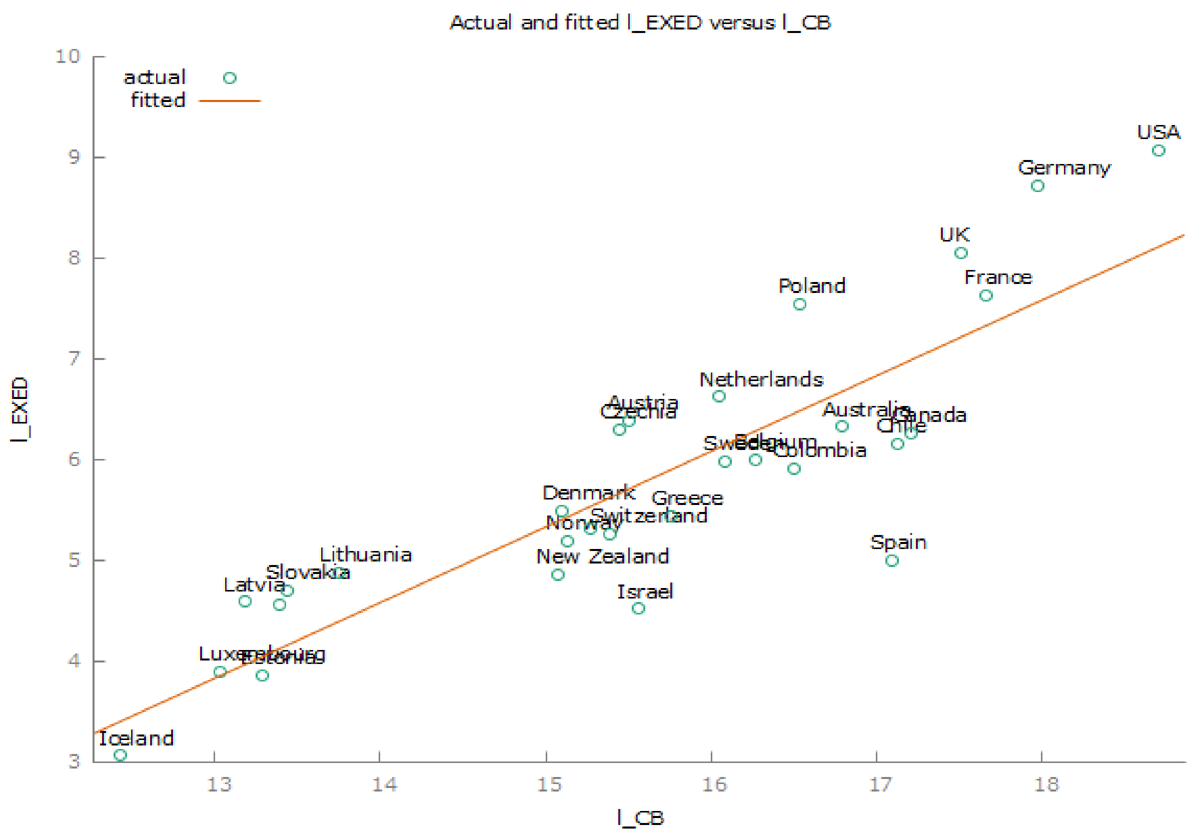

Figure 4: Regression $lAVEXED_i = a + blCB_i + e_i$

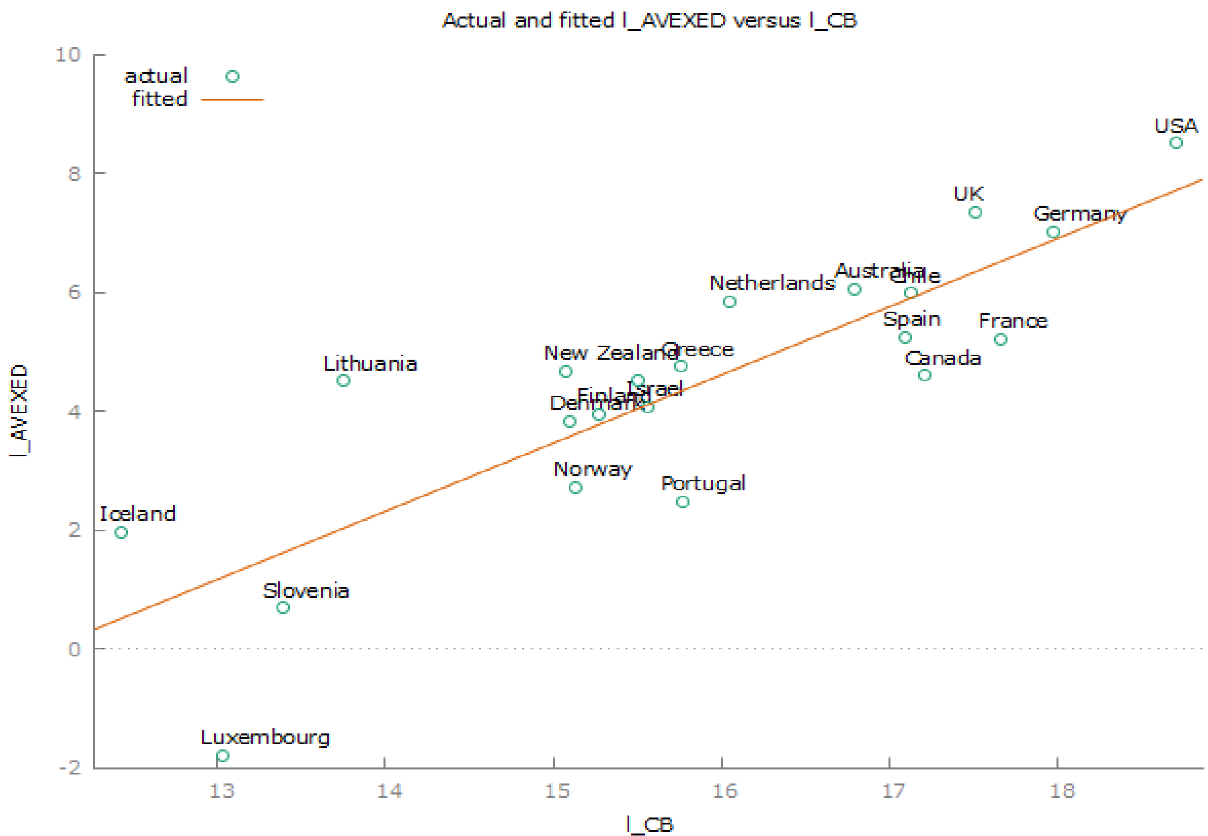

Figure 5: Regression $lEXED_i = a + blTOTALRECOVERED_i + e_i$

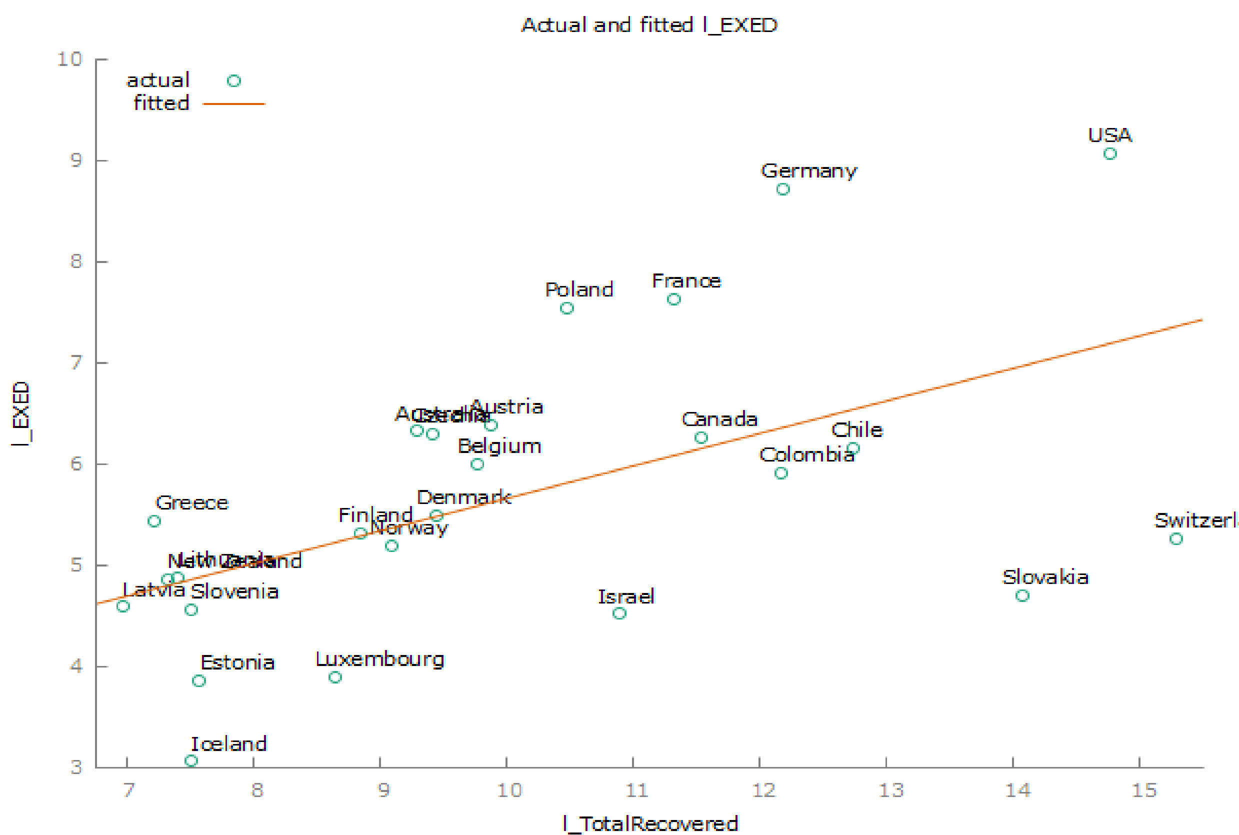

Figure 6: Regression $lAVEXED_i = a + blTOTALRECOVERED_i + e_i$

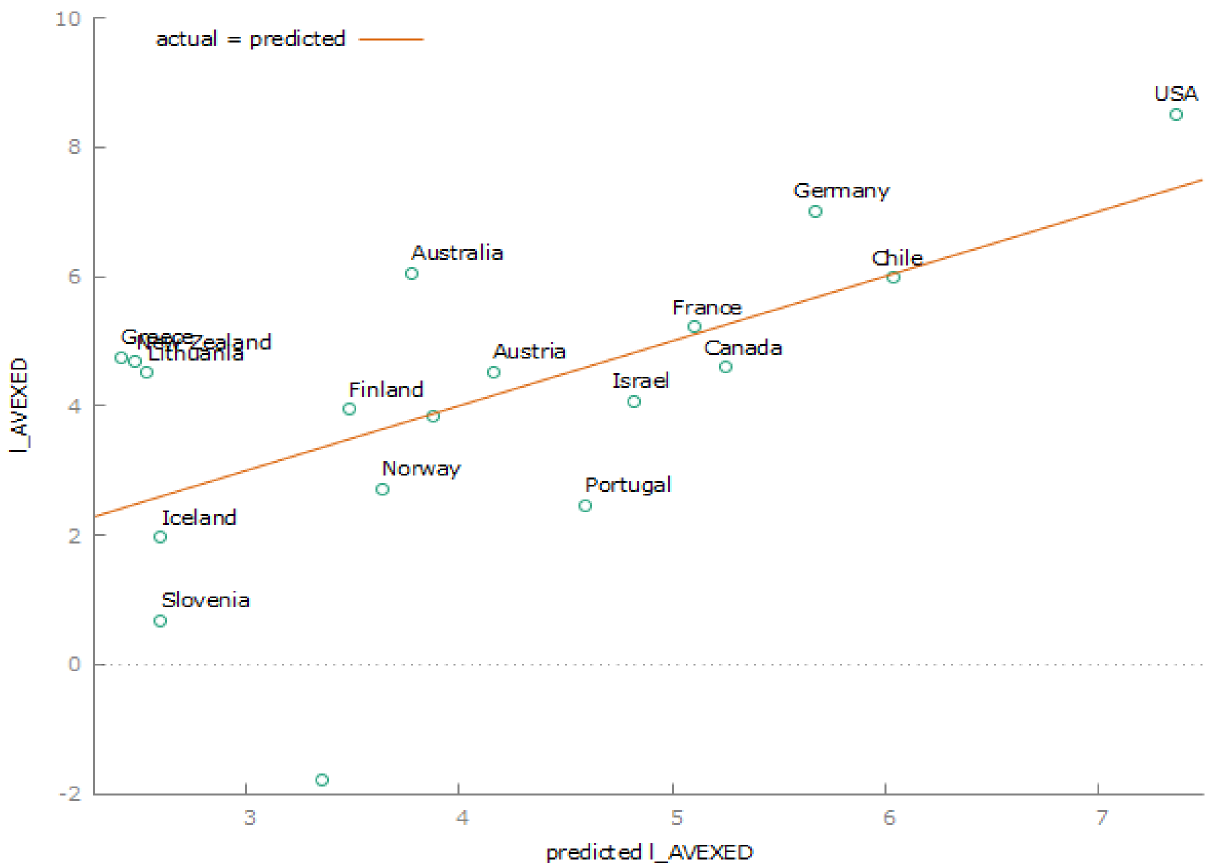

Figure 7: Regression $lEXED_i = a + blSTR_i + e_i$

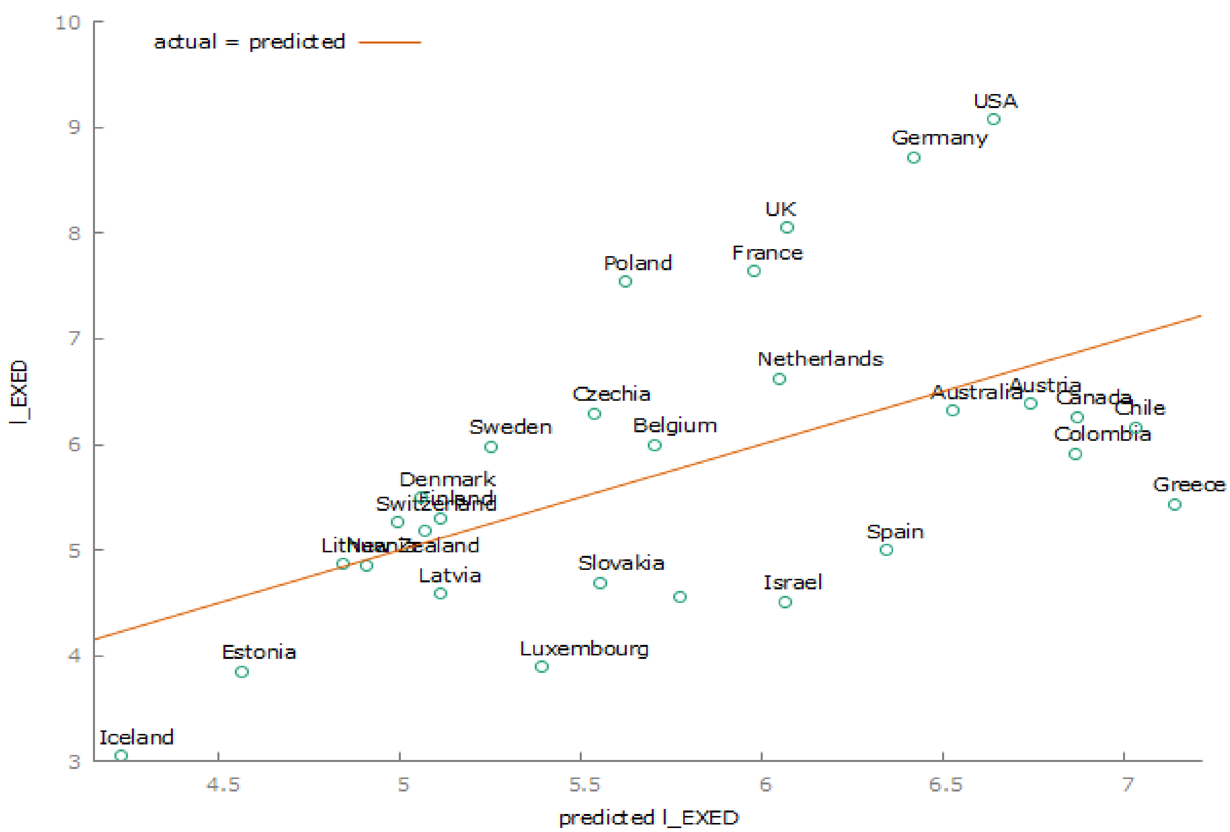

Figure 8: Multiple regression $lAVEXED_i = a+blCB_i+clPTI_i+dlTRUST_i+elGDPCAP_i+e_i$

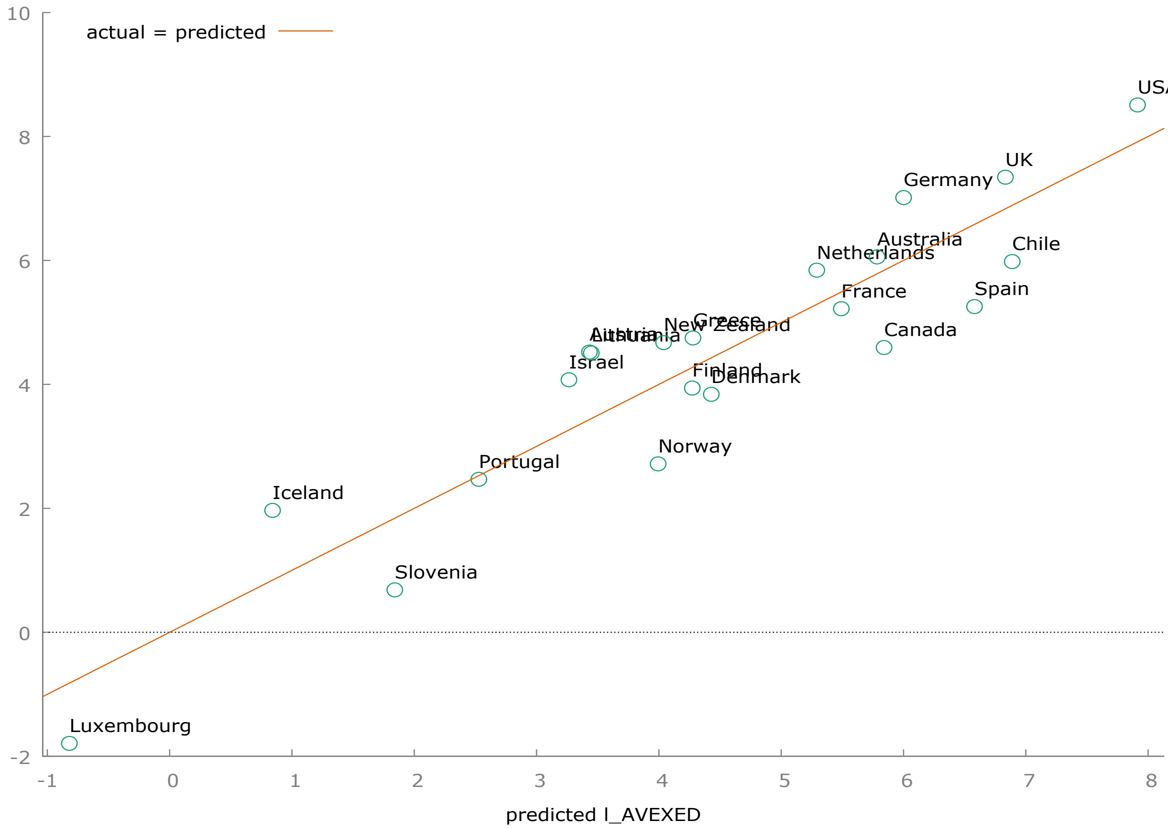

Figure 9: OECD $lAVEXED_i$ fitted against Actual lCB_i