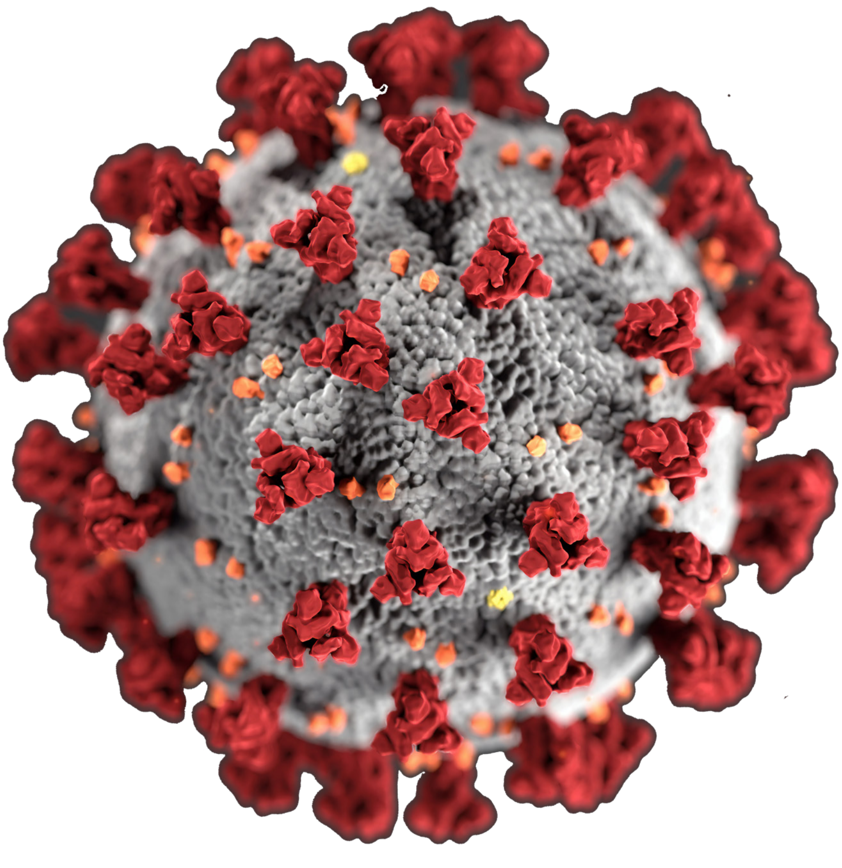
DEPARTMENT OF SCIENCE, TECHNOLOGY,
ENGINEERING AND PUBLIC POLICY

Tracking the impact of research on education policy during the COVID-19 pandemic



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STEAPP
WORKING
PAPER
SERIES

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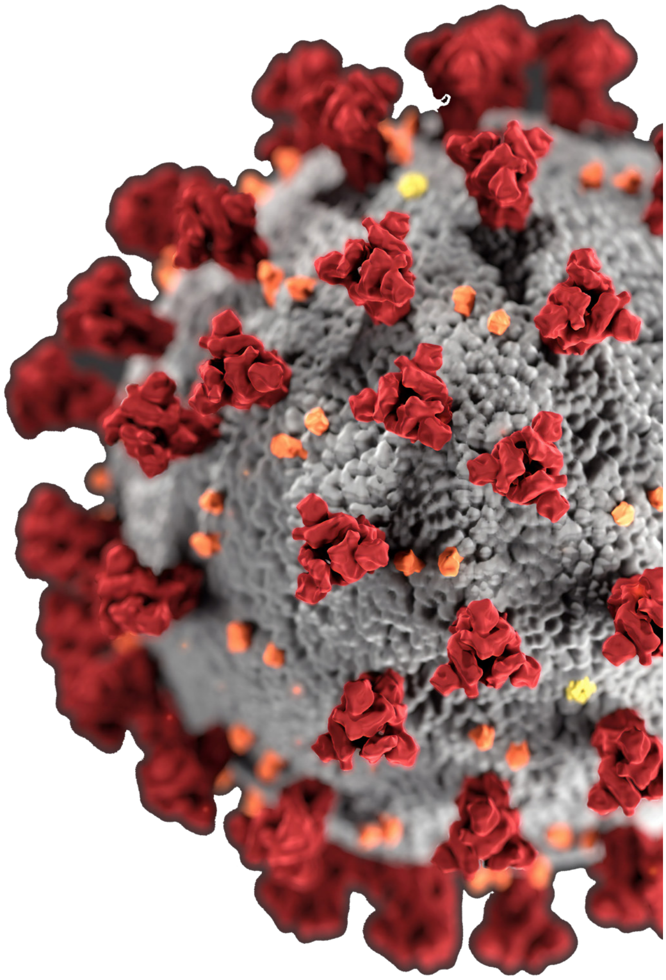

About the STEaPP Working Paper Series
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Abstract

School closures and other measures during the COVID-19 pandemic disrupted learning for more than 1.5 billion students (UNESCO, 2022). Education policymakers worldwide discussed these measures in thousands of policy documents, most of which reference academic research. The project seeks to analyse the scholarly citations of Covid-19 education policies and shed light on how governments used research during the pandemic.

Building upon the databases of Elsevier's International Centre for the Study of Research (ICSR) Lab and Overton, this case study applies scientometric methods to investigate if conventional research excellence metrics influence policy impact. Our methodology revolved around two regressions. The first was a logistic regression exploring how a paper's citation count, journal CiteScore, the lead author's h-index, and the Times Higher Education (THE) score for the lead author's institution influence whether a scholarly paper gets cited in policy. The second was an Ordinary Least Squares (OLS) regression to examine how the same four factors influenced the speed a scholarly paper was first cited in policy.

Results showed that policymakers used relatively narrow sources of research rather than drawing on the full range of available research. The analysis highlighted how policymakers utilised recent medical research more effectively than education research. Finally, we calculated no significant relationship between research excellence and policy impact, concluding that non-academic factors likely influenced which research policymakers used.

Keywords:

Public Policy, Scientometrics, COVID-19

Introduction

The COVID-19 pandemic was considered the “largest disruption to education in history” (Pearson, 2022). On average, schools around the world were closed for over four months, with one in ten countries closing their schools for more than nine months (Nature Editorial, 2022). This caused disruption to more than 1.5 billion students worldwide, disproportionately impacting the most vulnerable of them (Thorn & Vincent-Lancrin, 2021; UNESCO, 2022) .

These policies, which discuss school closures, mask mandates, lockdowns, online learning, and hybrid teaching among others, build upon and cite scholarly research. Leveraging ICSR Lab and Overton databases, this case study analyses scholarly and policy metadata to understand if there are differences between the research that was cited by policymakers, and research that was not.

We assume that if policymakers used the ‘best’ research, then they would have cited papers that have high citations in academia, are published in the most cited journals, are authored by top researchers, or conducted by the highest-ranking universities. Given these parameters, we seek to answer the two following questions:

- To what extent did governments use the ‘best’ research?
- How effective were governments in using the ‘best’ research?

Using Scopus, we identified over 430,000 scholarly papers about the coronavirus pandemic published since January 2020. While there have been bibliometric studies on the research output during the COVID-19 pandemic (Else, 2020; Viana-Lora & Nel-lo-Andreu, 2022; Wang & Tian, 2021), few have focused on analysing the utilisation of research in public policy using quantitative methods (Yin et al., 2021).

Without quantitative data on scholarly citations in policy, there is a knowledge gap in the understanding how scholarly research influences public policy. Only recently have large scale databases, such as Elsevier’s International Centre for the Study of Research (ICSR) Lab and Overton, can researchers begin analysing the dynamics between policy and research at scale. By focusing on education policy during the COVID-19 pandemic

By addressing the two research questions, our case study will help inform the development of indicators for measuring the abilities of policymakers at using evidence effectively. The indicators allowing us to compare and benchmark different governmental entities, across local, national, and international levels. Understanding the differences in the dynamics of using scholarly evidence between countries helps us identify best practices as well as possible challenges that may be disrupting the diffusion of academic research into policy.

Methodology and results

To understand the influence of each of these variables on policy impact, we ran a logistic regression where our dependent variable was whether a paper was cited in policy or not, and our independent variables were a paper’s citation count, the journal’s CiteScore, the lead author’s h-index, and the Times Higher Education (THE) research score for the lead author’s institution. We also ran a second regression for investigating to what extent research quality influenced how quickly a paper got cited in policy. In the second regression, we explored the influence of the same four independent variables, but this time on the speed of a scholarly paper’s policy impact.

The regressions aim to understand to what extent policy makers leveraged the best available scholarly research during the pandemic. The case study relies on data from Elsevier’s International Centre for the Study of Research (ICSR) Lab, which pools scholarly metadata from across all Eslevier’s data sources, and Overton, a global database of policy documents and their citations.

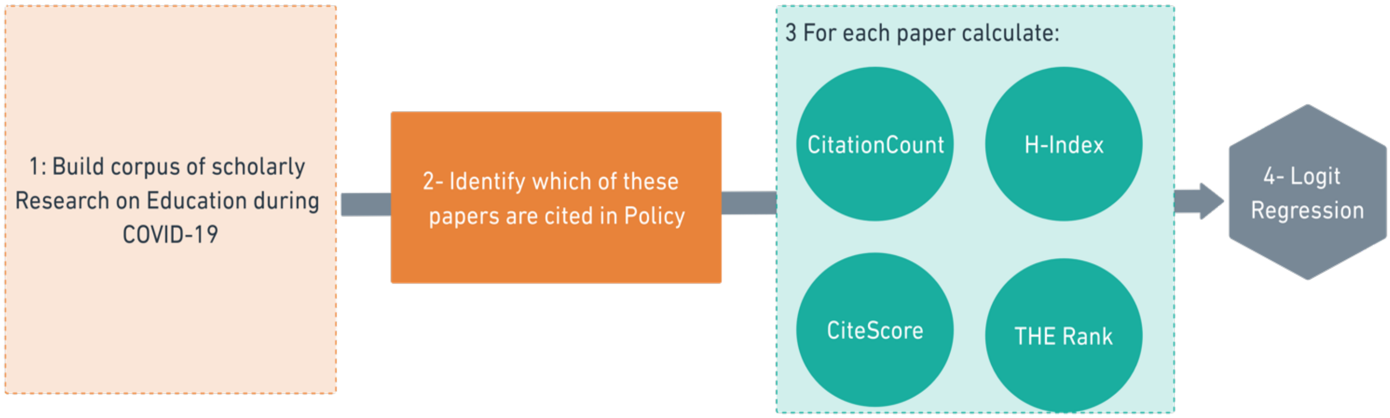

Figure 1 – Method for calculating to what extent did governments use the best science

Building a Corpus of COVID-19 Education Research

In collaboration with researchers at UCL's Institute of Education*, we developed a Scopus search query based on systemic literature reviews done on behalf of the UK Department for Education (Moss et al. 2021; Christie et al. 2021, Unterhalter et al. 2021; Spours et al., 2021) . We ran the query through Scopus in August 2022, identifying 4,615 scholarly articles published during the pandemic that studies various aspects of COVID-19 and education.

The query consists of four parts. First, we identified all papers with any mention of COVID-19, or its effects, in the title, abstract, or indexed keywords of articles (n= 432,745). The keywords consisted of COVID-19 and all the variations of the names as identified in the literature and in the Scopus database.

In the second stem, we limited the results to papers to those with mentioning a set of education keywords. The keywords were sourced from queries developed as part of systemic literature reviews commissioned by the UK Department for Education, in the title, abstract, or indexed keywords of articles (n= 26,453).

Since our focus is primarily on tracking the impact of education research on policy, in the third step, we excluded biomedical research related to COVID-19. This was done by manually searching all the top indexed keywords on Scopus that are linked to medicine or health (n=12,649). Finally, we applied a series of categorical filters by limiting the corpus to peer-reviewed articles published after 2019, and not by medical journals. The query, when run on Scopus on August 2022, returned 4,615 papers.

*Acknowledging Rachel France and Gemma Moss from UCL Institute of Education for their feedback and support in refining this query search.

TITLE-ABS-KEY({COVID-19} OR {SARS-CoV-2} OR {Severe Acute Respiratory Syndrome Coronavirus 2}OR Coronavirus* OR {Covid-19}OR {SARS Coronavirus}OR {COVID-19 Pandemic} OR "coronavirus 2019" OR "SARS-Cov-2" OR "nCov-2019" OR "sars cov 2" OR covid* OR "Social distancing" OR lockdown? OR Quarantin* OR "Self-isolation" OR {Coronavirus Disease 2019})

AND TITLE-ABS-KEY((Education OR E-learning OR Learn* OR Student? OR School* OR {Distance Learning} OR {Educational Measurement} OR "learning loss" OR Universit* OR {Education Program} OR {Education Programme} OR {Educational Status} OR {Academic Achievement} OR Teach* OR Curriculum OR "Lower secondary" OR "Junior secondary" OR "secondary school" OR "secondaries" OR "secondary education" OR "middle school" OR "Grade 6" OR "Grade 7" OR "Grade 8" OR "Grade 9" OR "Grades 6-9" OR "Year 6" OR "year 7" OR "Year 8" OR "Year 9" OR "Years 6-9" OR "Level 2 Education" OR "Key stage 3" OR "Key stage 4" OR P6 OR P7 OR P8 OR P9 OR Education OR "School clos*" OR "School reopening" OR School* OR "emergency remote teaching" OR "student-centred remote teaching" OR "emergency remote education" OR "student-centered remote teaching" OR "online pivot" OR "blended learning" OR "online learning" OR "hybrid learning" OR "remote education" OR "remote learning" OR "distance learning" OR "digital learning" OR "eLearning" OR "e-Learning"OR "crisis prompted distance education" OR "home learning" OR "homeschooling" OR "flipped learning" OR "flipped classroom" OR "distance education" OR "online education" OR "K-12" OR "middle school" OR "secondary school" OR school OR "high school" OR "R-12" OR "elementary school" OR "upper primary" OR "senior school" OR "years 4-11" OR "4-11 years" OR "year 1" OR "Year 2" OR "year 3" OR "year 4" OR "year 5" OR "year 6" OR Elementary OR "early years" OR "Primary school*" OR "primary schools" OR reception OR "first school" OR "foundation stage" OR "foundation primary" OR "key stage 0" OR "key stage 1" OR "key stage 2" OR "further education" OR "vocational education" OR "A level" OR "sixth form" OR "6 th form" OR "post 16 education" OR "tertiary education" OR "post-secondary" OR heis OR hei OR "higher education" OR "higher education Institution?" Universit* OR phd OR "research degree" OR masters OR pgcert OR graduate OR undergraduate OR postgraduate OR "student teacher")

AND NOT {Middle Aged} AND NOT {Very Elderly} AND NOT {Elderly} AND NOT {Nonhuman} AND NOT {Newborn} AND NOT {Infant, Newborn} NOT {Patient Care} AND NOT Pregnancy AND NOT{Adult} AND NOT "public health" AND NOT "non pharmaceutical" AND NOT pharmaceutical AND NOT pharmacy AND NOT clinic* AND NOT pathology AND NOT telemedicine AND NOT inflammation AND NOT patient* AND NOT neurology* AND NOT telehealth AND NOT Telemedicine AND NOT surgery AND NOT employee? AND NOT {Prevention And Control} AND NOT {Coronavirus Infections} AND NOT {Coronavirus Infection} AND NOT {Virus Pneumonia} AND NOT {Pneumonia, Viral})

AND PUBYEAR > 2019 AND DOCTYPE(ar) AND (EXCLUDE (SUBJAREA,"MEDI"))

Figure 2 – Scopus Advanced Search Query String

Data Wrangling using ICSR Lab

We matched each publication identified on Scopus with its metadata on ICSR Lab using the Digital Object Identifier (DOI). We used the March 2022 snapshot (v7) of ICSR Lab, which excluded the 30% of articles that were published after that date.

For the remaining 3,188 articles, we identified the papers that were cited at least once in policy (n=178), we also calculated their citation count and the CiteScore of the journal the papers were published in. We then extracted the lead authors' unique IDs, cross referencing those with the entire ICSR database to calculate their h-index. We excluded 22% of the papers that did not have an author ID or CiteScore. Finally, we identified the institutional affiliation of each lead author.

Although an institutional score could be calculated directly using ICSR data, we chose to use the 2020 Times Higher Education (THE) institutional research scores mainly because they also use Scopus data, which would be more compatible with our existing dataset (Elsevier, 2021). However, THE provided the intuitional scores per university without matching institutional IDs. As a result, we had to join the databases by university name only, which caused a major challenge due to name disambiguation (e.g. UCL vs University College London). Although we applied multiple algorithms to match THE scores with our main dataset in ICSR Lab, we were unable to match 56% of our corpus. Fig 3 Below highlights the data loss at each step of the data wrangling process.

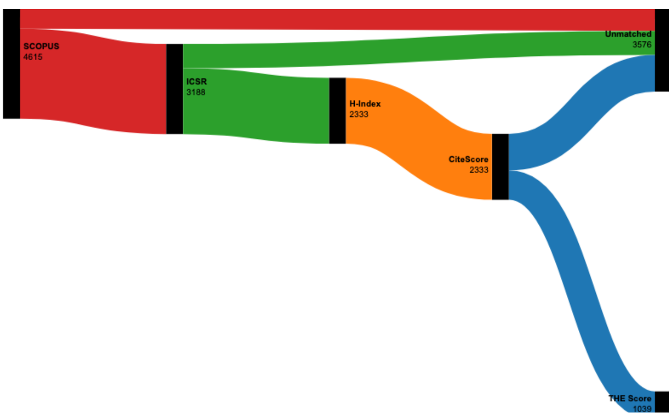

Figure 3 – Data loss at each methodology step

Keyword co-occurrence mapping

Once our dataset was cleaned and compiled, we ran an initial exploratory data analysis to uncover fundamental differences between the papers cited in policy, and those that were not. First, we performed a term co-occurrence analysis using VOSviewer (van Eck & Waltman, 2022). We ran the analysis separately on our entire corpus (Figure 4) and the subsection of the research cited in policy (Figure 5) to help us understand the topical differences between the two sets.

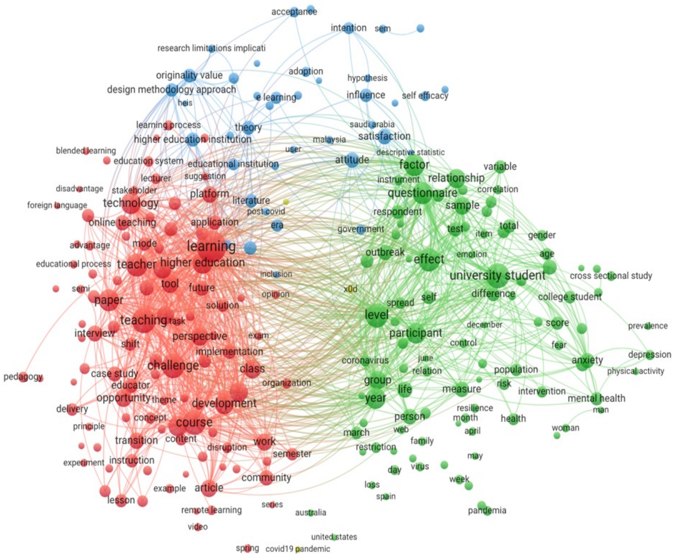

Figure 4 – Term co-occurrence map for all COVID-19 education research

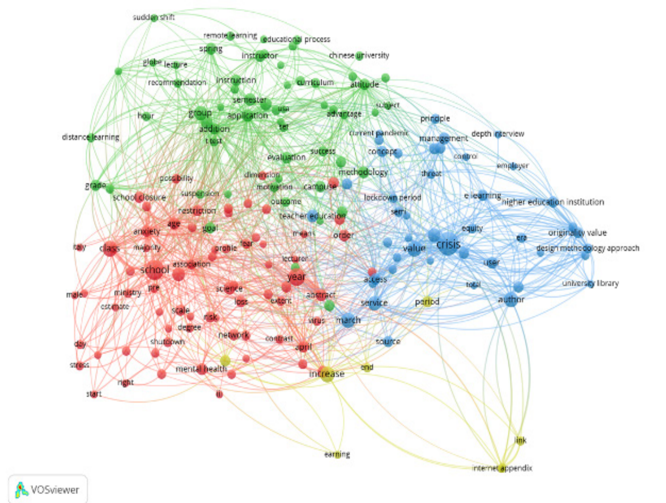

Figure 5 – Term co-occurrence map for COVID-19 education research cited in policy

The term co-occurrence algorithm run on the entire corpus, displayed in Fig4, highlights the 60% most relevant terms that appear in at least 30 papers. The analysis finds two main clusters, the first (green) focusing on the impact of COVID-19 on the wellbeing of students featuring terms such as “effect”, “anxiety” and “mental health”. The second (red) cluster the impact of COVID-19 on the education system, with terms such as “learning”, “teaching”, and “online teaching”.

At the surface level, the map in Fig 5, which was run on the subsection of papers cited in policy, shows that there was no major thematic difference between research output and research cited in policy. Policymakers cited the main themes highlighted in the entire corpus, such as the impact of COVID-19 on student wellbeing, citing papers featuring “school closure”, “anxiety”, “mental health”, and “fear, as well as the impact of the pandemic on education, citing papers featuring “curriculum”, “instruction” and “remote learning”. Further investigation is required to understand the topical difference between research supply and policy demand for evidence.

Geography of Evidence

The second analysis focused on differences in the geographies between papers cited in policy and papers that were not. Using ICSR Lab, we matched each lead author to the country of their institution. Figures 6 and 7 below highlight the country of origin for both groups.

We find that papers cited in policy come from a much smaller pool of countries, with most citations coming from the European Union (31%), United States (17%), the UK (9%). Further, while 40% of the research on education during Covid-19 was led by authors in low and middle income countries (World Bank Group, 2022),they account for less than 16% of papers cited in policy. Although this may point to an existing notion of bias against research from the global south(Amarante et al., 2022; Harris et al., 2015), it is more likely that the discrepancy is caused by skewed data. Overton is more effective at indexing English language policy documents from developed countries (Szomszor & Adie, 2022), which is why our study is mostly tracking citations of scholarly work in policies drafted by developing countries. Finally, because education is localised, with different countries, and often different local-entities having differing educational systems and curricula, research findings in one country may not be applicable in the context of another country.

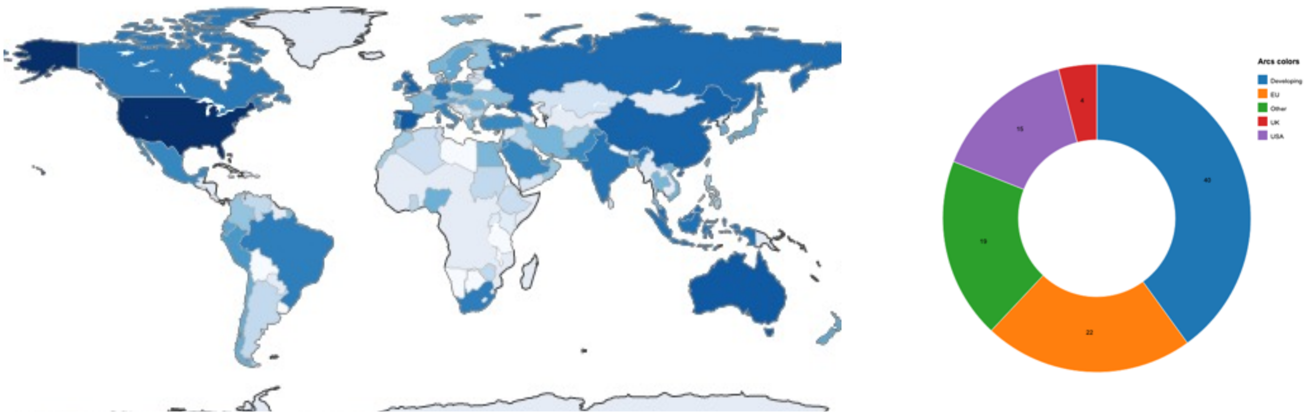

Figure 6 – Lead author countries for all COVID-19 education research

Figure 7 – Lead author countries for COVID-19 education research cited in policy

Logit Regression: the influence of research excellence on policy impact

We analysed our corpus in to understand if there were differences in the distribution of academic citations, CiteScores, author h-index, and institutional THE score between papers cited in policy, and those not cited in policy. We display the differences in Figure 8, below, with “1.0” representing papers cited in policy, and “0.0”, representing papers not cited in policy.

We found that scholarly papers cited in policy tended to also have more academic citations, be published in journals with higher CiteScores, and from authors with higher h-indexes. For institutional THE Score, we found that while both sets included universities from all ranks, the papers cited in policy included a higher distribution of authors from higher-ranked institutions.

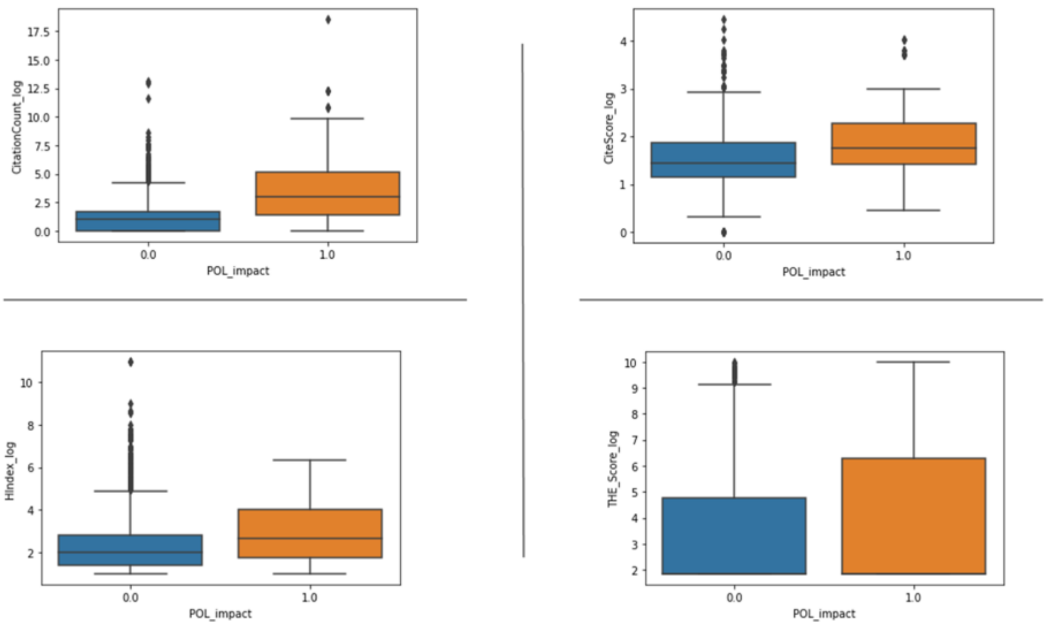

Figure 8 – Bibliometric differences for papers with policy impact

We then ran a logistic regression using the normalised values of our variables. The regression results, displayed in Figure 9, show that citation count was between five and ten times more likely to influence whether a scholarly paper is cited in policy than the three other variables. The finding is a surprising result, mainly because papers need many years to accrue citations, meaning that the citation count at the time of analysis is just a fraction of the total citations the paper will accrue over time.

```
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         Iterations 5
                           Logit Regression Results
==============================================================================
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Method:                           MLE   Df Model:                            3
Date:                Sat, 03 Sep 2022   Pseudo R-squ.:                  -2.491
Time:                        15:42:55   Log-Likelihood:                -642.61
converged:                       True   LL-Null:                       -184.10
Covariance Type:            nonrobust   LLR p-value:                     1.000
=======================================================================================
                          coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------------
z_CitationCount_log     0.3482      0.078      4.483      0.000       0.196       0.500
z_HIndex_log            0.0347      0.070      0.495      0.621      -0.103       0.172
z_CiteScore_log         0.0550      0.069      0.792      0.429      -0.081       0.191
z_THE_Score_log         0.0682      0.068      1.008      0.313      -0.064       0.201
=======================================================================================
```

Figure 9 – Summary of Logistic Regression Results

Despite citation count's relative influence compared to the other variables in the study, with a coefficient of 0.3448, citation count remains a relatively poor predictor of policy impact. Further, we masked 70% of the data, using a machine learning model trained on a random set of 30% of the observations to predict which masked papers would get cited in policy. After conducting 20 attempts, we found that the model had poor precision (best score = 0.5) and recall (best score = 0.33). If the 'best' science is measured by conventional research excellence metrics, then this regression concludes that other, non-academic, factors play a greater influence on determining whether a paper will get cited in policy, or not.

Speed of Scholarly Impact on Policy

We also ran an OLS regression for measuring how the speed of a scholarly paper's policy impact, defined as the time between the date of publication of the cited scholarly article and the date of publication of the citing policy document, is influenced by a paper's citation count, journal CiteScore, the lead author's h-index, and the THE score for the lead author's institution. As the regression is focused on speed of policy impact, we excluded all research that was not cited by policy. We also had no limitation in terms of academic field, so we are interested in all the scholarly articles cited by education policy during COVID-19, not just the education research.

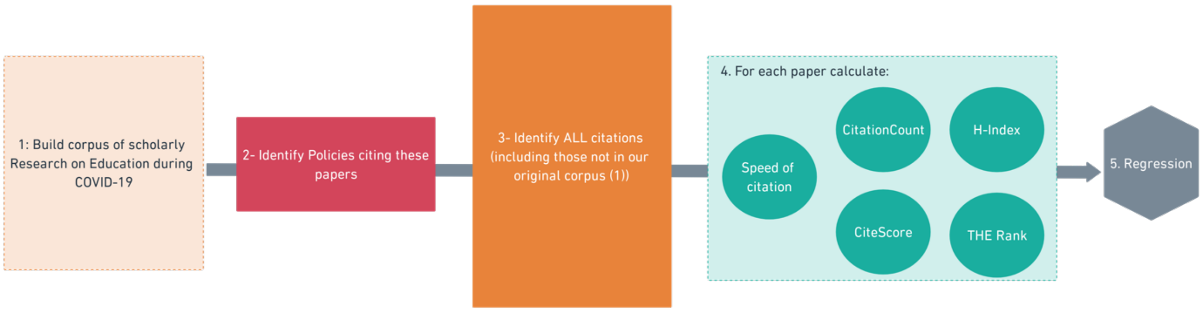

Figure 10 – Method for OLS regression

We took the same corpus of 4,615 scholarly articles identified in Scopus, but instead of using ICSR Lab to identify the subsection of the papers that was cited in policy, we extracted the DOIs of the entire corpus and run them through Overton to identify the actual policy documents that cite this research (n = 206). We then extracted all the policy documents' citations (n = 10,952) and matched their metadata in ICSR Lab, following the same steps as with the first regression to calculate CiteScore, the lead author's h-index, and the THE score for the lead author's institution.

Following an initial data analysis, we saw that despite an abundance of evidence published during the pandemic, over 42% of the policy citations were to scholarly papers published before 2020. Fig11 below highlights the distribution of scholarly evidence cited in our policy corpus by date.

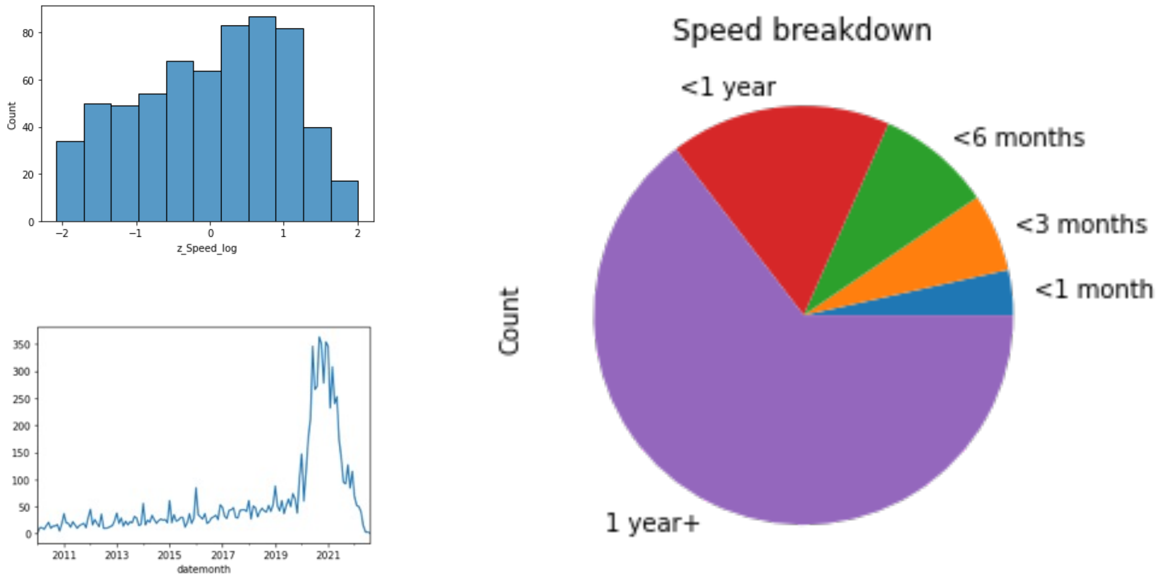

Figure 11 – Distribution of scholarly evidence cited in our policy corpus by date.Top left is the normalised distribution of the number of papers cited in the policy corpus after 2020. Bottom left shows the histogram of all papers cited in policy corpus by year. Right shows the relative distribution by date

We also found that there was a significant topical difference between cited papers published before and after 2020. Fig12 below shows the term co-occurrence map for all the scholar papers cited in our policy corpus overlayed with their date of publication. We find that policymakers cited recent (yellow) medical research, featuring keywords such as “coronavirus disease”, “infection”, and “outbreak”, but that education papers with keywords such as “teaching”, “student” and “learning”, were mostly published before the pandemic.

This is a surprising result, because our original corpus identified over 4,615 research papers focused on education during COVID-19, of which 3% were cited by policy-makers. The large pool of uncited education policy papers could a discrepancy in the way policy makers accessed relevant educational research during the pandemic. For example, Gurdasani et al (2022) argue that the UK’s education policy was an international outlier, with government selectively choosing evidence that supported political narratives. The next phase of the research will further explore differences between policy demand and research supply.

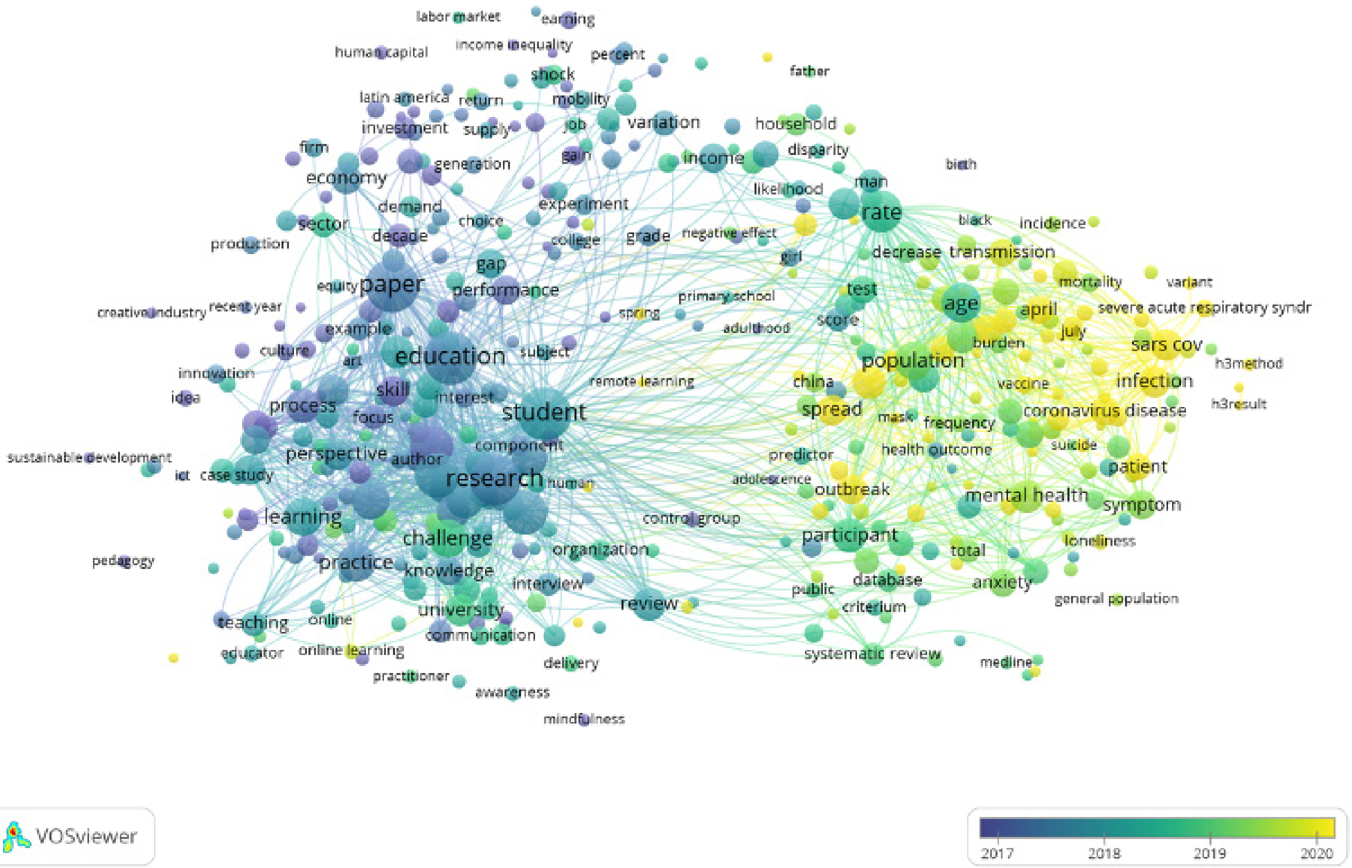

Figure 12 – Keywords co-occurrence for scholarly papers cited in

We also examined the extent to which evidence was shared between the European Union (EU), United Kingdom (UK), United States of America (US) and International Organisations. For each country, and extracted the DOIs of their citations and then compared whether those DOIs were present in the citations of other countries. We found that less than 1% of scholarly papers were shared by all four entities. Even when comparing citations bilaterally, the highest rate of evidence shared by two entities was slightly over 10%. We also found a clear preference for policymakers to cite research from their own countries, which is reasonable because education is highly localised, meaning policymakers needed more contextualised evidence.

	% references in International Organisations policies shared	% references in USA policies shared	% references in UK policies shared	% references in EU policies shared
IGOs	N/A	10.6%	12.57%	13.5%
USA	4.1%	N/A	5.4%	4.2%
UK	3.9%	4.3%	N/A	5.4%
EU	4%	3.16%	5.13%	N/A
Common	**0.62%**			

Figure 13 – Evidence sharing between political entities

OLS regression results

The regression measured the influence of four independent variables, a paper's citation count, journal CiteScore, the lead author's h-index, and the THE score for the lead author's institution, on how quickly the paper was cited in policy. Figure 14 highlights the differences in distribution of the four independent variables between papers cited within 3, 6, and 12 months of publication.

It is not surprising to see that younger research papers cited in policy have fewer academic citations. It takes time for research to be recognised within the academic community, and then for other academics to publish papers including these citations. We also found no significant difference in THE score of institutions at different time intervals. The distribution of the h-index of authors, however, tended to fall over time, as did the CiteScore of the publishing journal.

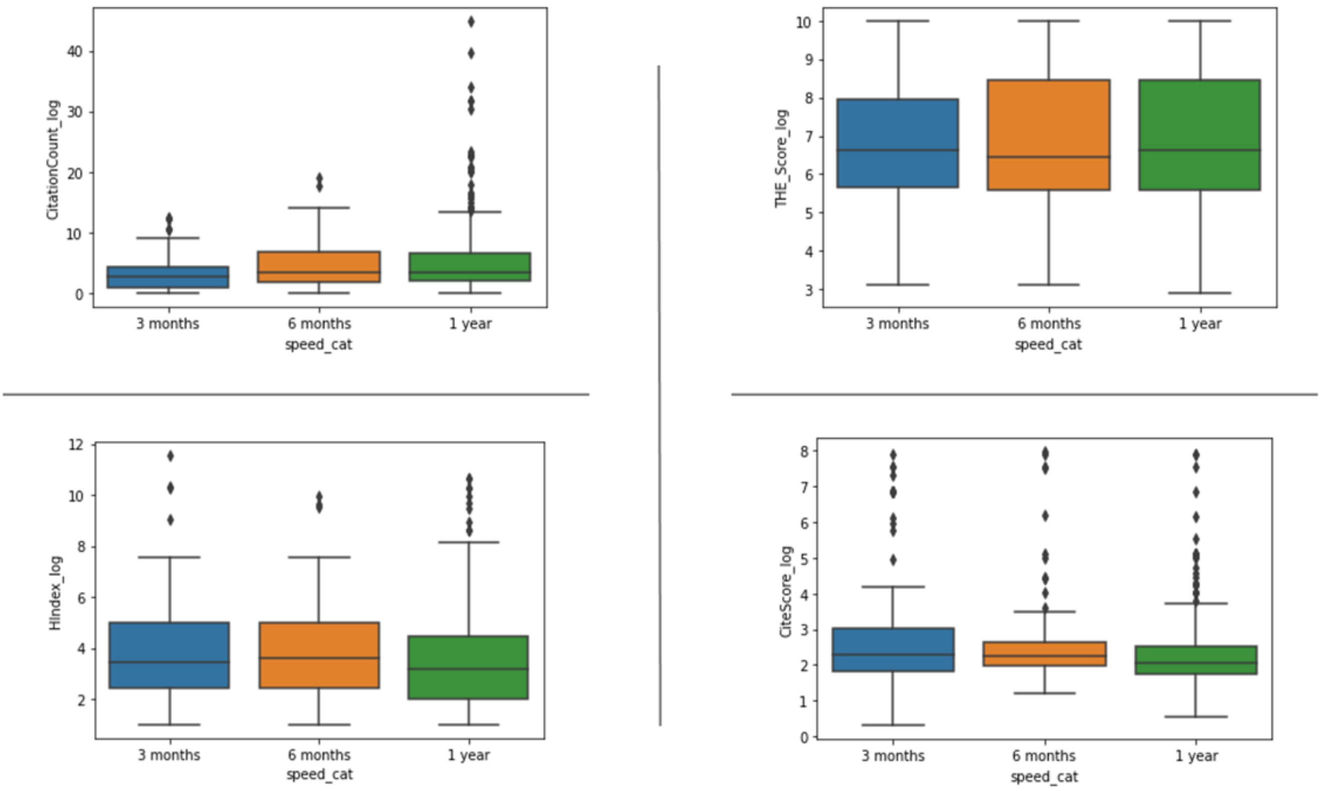

Figure 14 – Differences between papers cited within 3, 6, and 12 months of publication

The regression results confirm our visual analysis. They show an inverse relationship between citation count and speed of impact. We also found an inverse relationship between speed of impact and THE scores, but with a coefficient of 0.0376 the influence seems marginal. Both h-index and CiteScore influence the speed of impact, but both had relatively low coefficients. Ultimately, with an R-squared value of 0.1, the model was a poor fit overall.

As a result, we could conclude that there is no clear relationship between conventional metrics for research excellence and the speed in which scholarly evidence is cited by policy. Other, possibly non-academic factors play a role in determining how quickly research reaches policymakers.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            z_Speed_log   R-squared:                       0.100
Model:                            OLS   Adj. R-squared:                  0.095
Method:                 Least Squares   F-statistic:                     17.37
Date:                Sun, 04 Sep 2022   Prob (F-statistic):           1.61e-13
Time:                        20:29:40   Log-Likelihood:                -857.90
No. Observations:                 628   AIC:                             1726.
Df Residuals:                     623   BIC:                             1748.
Df Model:                           4
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept            1.813e-16      0.038   4.77e-15      1.000      -0.075       0.075
z_THE_Score_log         0.0376      0.040      0.941      0.347      -0.041       0.116
z_HIndex_log           -0.0869      0.041     -2.139      0.033      -0.167      -0.007
z_CiteScore_log        -0.2310      0.042     -5.539      0.000      -0.313      -0.149
z_CitationCount_log     0.2630      0.040      6.594      0.000       0.185       0.341
==============================================================================
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Figure 15 – Summary of OLS regression results for Speed of Impact

Discussions and lessons learnt

Large scale quantitative research on policy impact is a nascent field, with few tested methods. Many of our approaches are experimental, requiring trial and error and resulting in lessons learnt after facing obstacles with the data and methodology.

First, our scholarly corpus is limited to peer-reviewed articles published in journals that are indexed by Scopus. Unlike other bibliometric databases, Scopus has inclusion criteria, mostly focusing on quality. Given the crisis, a significant amount of research was published in alternative formats, but still had policy influence. For instance, Fraser et al. (2021) outline the growing importance of preprints in spreading the latest research during the pandemic. Preprints and other papers not indexed in Scopus were excluded from our analysis.

It is important to note that analysing policy citations measures a small portion of how research influences policymakers. Researchers influence policymakers in many ways, such as speaking in committees, providing direct advice to decision makers, attending conferences, or advocating through the media, which is not captured in our analysis. We also do not know the extent of Overton's coverage, with an unknown number of policy documents that are not captured in our dataset. Further, of the policy documents identified, over half do not have any citations, while a significant percentage of citations (25% in our corpus) are to other policy documents, not scholarly papers.

Second, there are also structural issues with our regressions. Citation count, which has significant influence in both our regressions, is a misleading indicator. Our scholarly papers represent multiple disciplines, each with their own citation patterns. An academic citation for a paper in a niche field where citations are rare, is far more valuable than a citation from a larger field. Moreover, due to the structure of the ICSR lab, our citation counts include academic citations that occur after the scholarly paper had been cited in policy.

A possible solution is replacing citation counts with Field Weighted Citation Impact (FWCI) metrics. FWCI will help reduce bias caused by different citation behaviour across different domains. Further FWCI enables us to use predicted metrics to overcome the fact that many of our papers have low citations, which is why the OLS regression showed an inverse relationship between citation count and impact speed.

Further, we used the h-index and THE scores of the lead author only, which eliminates the role of co-authors on policy impact. This is particularly problematic because lab directors and senior researchers are often listed as co-authors, and play an important role in sharing their lab's research results to policy-makers. In the next phase, we will explore how using the average h-index and THE scores of all co-authors, or the scores of the highest co-author affects our model.

There is also an issue with multicollinearity. CiteScore, h-index and THE research score are metrics derived from article citations, which results in varying degrees of correlation between them. While the correlation level is relatively low, with the highest coefficient being 0.29 between h-index and CiteScore, more work is needed to control for the impact of multicollinearity.

Another issue with the regression is our assumption that the relationship between our dependent and independent variables is linear, which may not be accurate. In the next phase, we will explore non-linear regression models as well as adding new variables, such as media coverage, to improve the model's fit and accuracy.

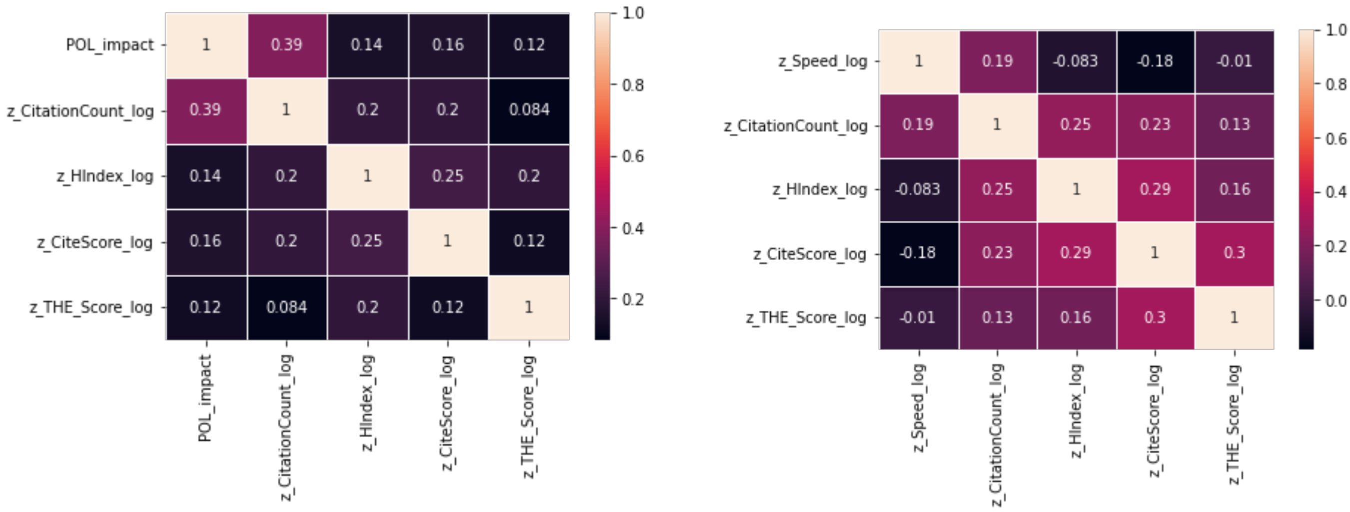

Figure 16 – Correlations between variables for logit (left) and OLS regression (right)

Finally, and perhaps most critically, policies citing our scholarly corpus were not all relevant to education policy during COVID-19. For example, over 35% of policies are categorised under “business” and “labour” policy, which do not directly deal with topics such as school closures or hybrid learning during the pandemic. Further, using various search tactics on Overton, we identified a significant portion of COVID-19 education policies that did not cite our initial scholarly corpus.

As a result, in the next phase of the case study, we will reverse engineer our methodology. Instead of first building a corpus of research papers focused on education during COVID-19 in Scopus and then tracing their policy citations, we will start by using Overton to identify relevant COVID-19 education policies and then trace their scholarly citations using ICSR Lab. This should provide a more reliable corpus for analysis.

Conclusion

Despite limitations in the methodology, initial results point to systemic issues with how policymakers use scholarly evidence. We found that policymakers tended to use relatively narrow sources of research, primarily citing sources from their own countries, rather than drawing on the full range of available and relevant research. The analysis also highlighted a difference between research fields, with policymakers more effectively utilising recent medical research, but not the latest education research. Finally, we found a weak relationship between research excellence and policy impact, concluding that non-academic indicators play a large role in determining which research gets used by policymakers.

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