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Education for All? Assessing the Impact of Socio-economic Disparity on Learning Engagement During the COVID-19 Pandemic in Indonesia

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Abstract: *This paper attempts to shed light on the impact of socio-economic disparity on learning engagement during the COVID-19 pandemic in Indonesia. Utilising search intensity data from Google Trends, school data from Dapodik (Education Core Database), and socio-economic data from the National Socioeconomic Survey, we conduct descriptive analysis, an event study, and difference-in-difference estimations. First, school quality differs in terms of the regions' development level, especially between western and eastern Indonesia. However, densely populated and well-developed areas generally have lower offline classroom availability. In addition, the quality of public schools is generally lower than private schools. Second, our estimation results show that only online-classroom related search intensity that increased significantly after school closures on 16 March 2020, not in self-learning related search intensity. Further the analysis shows that socio-economic disparity within provinces widens the gap in online learning engagement, albeit with weak evidence from per capita expenditure. Interestingly, provinces with a higher inequality and rural population tend to have higher self-learning related search intensity due to students' necessity to compensate for low learning quality from schools. In addition, technology adoption does not seem to give much of an increase to online-classroom related search intensity but contributes to lower self-learning related search intensity due to increased academic distraction. Our study provides evidence for the Indonesian government to make more precise policy in improving learning quality during the pandemic.*

Keywords: Covid-19 Impact, Education Inequality, Online learning
JEL classification: I24, O15

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1. Introduction

As a response to the COVID-19 pandemic crisis, the Indonesian education sector has been forced to adopt remote learning to reduce the possibility of infection and accommodate distancing protocols. However, many have questioned its effectiveness (Esposito and Principi, 2020; Iwata, Doi, and Miyakoshi, 2020) as there are growing concerns that lower-income students and less-developed regions are not well prepared for the unprecedented shift in learning style. First, glaring issues on the digital divide between regions can potentially hinder the effectiveness of distance learning as some people lack adequate internet access. Second, low-income students will be more disadvantaged due to the lack of access to good schools and their lack of technological tools, such as laptops and smartphones, to access the teaching modules. In addition, the economic shocks from the pandemic contribute to the loss of learning outcomes. These concerns have led the Indonesian government to plan a physical classroom re-adoption scheme with limited classroom capacity, which leads to the third concern: Do schools have adequate capacities to prepare themselves according to new policies? As the government is still searching for the most appropriate way to tackle these issues, it is important to have a better understanding of the impact of socio-economic disparities on learning effectiveness, both distance learning and limited capacity classroom teaching.

This paper attempts to shed light on the impact of socio-economic disparity on learning effectiveness during the COVID-19 pandemic in Indonesia. There are two main analyses that will be carried out in this paper: 1) we aim to provide descriptive information in terms of schools' ICT and other physical infrastructure; and 2) conduct a series of event study estimations and difference-in-difference approaches on search intensity, as a proxy of online learning engagement, by socio-economic characteristics and technology adoption.

These analyses are made possible by our extensive school database, which captures information on all schools in Indonesia. We constructed the database by web scraping the Education and Cultural Main Database/Dapodik. We also apply search intensity from Google Trends to capture the online learning engagement from related keywords. We initially identify the most relevant keywords concerning online learning for both online classroom and self-learning related activities. In addition, we utilise the Indonesian Socioeconomic Survey (Susenas) for household characteristics in the region. To our knowledge, there are still only a limited number of studies that utilise school databases, and none in Indonesia has ever utilised search intensity on Google Trends to evaluate learning engagement.

Indonesia has mandated the distance learning scenario since 16 March 2020[4] to mitigate the COVID-19 spread in Indonesia. However, this regulation poses challenges for schools located in regions lacking digital infrastructure and training for new methods of teaching. The Ministry of Education reports that the share of schools at all levels of education that have adopted distance learning in regions such as Aceh, Papua, Nusa Tenggara Timur, and Bangka Belitung is still below 60%.[5] This is in contrast with Java, where more than 90% of schools have adopted distance learning.

Transitioning to the new normal period, several schools located in low infection areas have been allowed by the Ministry of Education to resume in-person classes, although flexibility to this policy remains applicable.[6] However, school opening depends on local government regulations, which continuously change over time due to the ever-changing COVID-19 situation that also varies across regions. Despite the Ministry of Education's efforts to devise emergency curricula during this time to help teachers, students, and parents in conducting distance and in-person learning, the already differing school infrastructure and student socio-economic backgrounds can have potentially severe implications for learning effectiveness and educational outcomes.

2. Literature review

Indonesia's socio-economic inequality and educational outcomes are reflected in the country's regional disparity, especially between the eastern and western parts (Azzizah, 2015). Several regions outside Java are plagued with low infrastructure and digital access, which further exacerbates the socio-economic

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[4] This regulation is mandatory and should be applied universally in all Indonesian schools. https://www.bbc.com/indonesia/indonesia-51769074.

[5] http://sekolah.data.kemdikbud.go.id/kesiapanbelajar/pbm

[6] https://www.cnbcindonesia.com/news/20200906080949-4-184675/mas-nadiem-kapan-sekolah-bisa-masuk-lagi-ya

disparities and, therefore, creates larger losses in learning outcomes. As an illustration, the latest information from the Indonesian Socioeconomic Survey (Susenas) on March 2019 shows that despite almost 90% of Indonesian household having access to mobile phones, only 65% of them have access to the internet. In addition, broadband internet access coverage is still low, especially in rural areas and the eastern part of Indonesia. Whereas areas like Java has 48.26% of their population connected to the internet, only 24% of the total Papua population has access to such infrastructure.[7]

It is widely agreed that teachers' physical presence plays as an important role in schools (Suryadarma, et al., 2006; Duflo and Hanna, 2005). Moreover, amid crisis periods, student enrolment has been found to significantly decrease, thus harming younger children (Thomas et al., 2004; Andrabi, Daniels, and Das, 2021). However, several studies from the education research field have also found that distance learning generates the same outcomes as physical teaching, both for education quality and social satisfaction (Tamim et al., 2011; Kim, Kwon, and Cho, 2011).

However, previous studies are unable to capture the current COVID-19 pandemic crisis as they cannot account for the effect of the unprecedented shift in teaching methods, and the crisis is not solely a financial crisis but also a health crisis. For the case of the United States (US), Kuhfeld et al. (2020) projected learning loss in both reading skills and mathematical skills during distance learning because of COVID-19. In addition, socio-economic gaps have been found to exacerbate education outcomes as lower-income students receive larger and more persistent learning loss (Chetty et al., 2020; Hamilton et al., 2020; Acuejo et al., 2020). Most of the reasons for the learning loss have attributed to the larger economic downturn experienced by lower-income students, which is consistent with the fact that education spending in lower-income households is largely reduced and substituted to other expenses in the case of economic shocks (Banerjee and Duflo, 2007; Das et al., 2013).

[7] Susenas, March 2019.

There is still limited literature on learning effectiveness during this pandemic in the context of Indonesia. The most related literature comes from Alifia et al. (2020), who conducted phone surveys to capture the distance learning experience in Indonesia. They found not only that the lack of digital access has become a barrier but also that the lack of learning facilities and parent support is contributing to the issue. The lack of support also highly correlates with socio-economic status. However, the literature on assessing socio-economic status and distance learning is still non-existent.

A recent study in the US emphasised how socio-economic difference and digital technology divide could further widen the gap in learning effectiveness during this pandemic, using search-intensity data (Backer-Hicks, Goodman, and Mulhern, 2021). We mainly adopt the methodology from this paper in our study. Other feasible alternatives that we could use are the usage of social media and internet search trends, which have been utilised in past literature, such as Choi and Varian (2012) who predict future consumer behaviour using google search trends. For the case of Indonesia, most of the existing literature uses this method for observing sentiment effects. For example, UN Global Pulse (2014) uses social media conversation as an information pool of sentiments towards fuel subsidy removal and food price shocks. Although social media trends can provide us with more granular observations, we find that social media searches have too much noise as they largely capture marketing buzz, political issues, and other issues that are relevant to companies and other stakeholders, thus providing us with imprecise indicators. Therefore, we stick to Google search trends as our proxy for online learning engagement.

3. Data and methodology

3.1. Data description

The Indonesian school database was obtained through a web-scrapping method from various websites. We gathered the data from the Education and Cultural Main Database (Data Pokok Pendidikan-Kebudayaan/Dapodik) by the Indonesian Ministry of Education and Culture for the year 2019 (http://dapodik.data.kemdikbud.go.id/). The database captures information on all schools in Indonesia, including their location at the village level, the number of teachers and students, number of classrooms, laboratories, sanitation, internet access, and other facilities.

Based on the constructed education dataset, there were 219,746 schools registered under the Indonesian Ministry of Education and Cultural Affairs (MoEC) in 2019, excluding those located overseas, with 44,758,220 active students. Of these, 68% are primary school or equivalent (Sekolah Dasar (SD)), and 18% are junior secondary (Sekolah Menengah Pertama (SMP)), while senior secondary (Sekolah Menengah Atas (SMA) and Sekolah Menengah Kejuruan (SMK) comprised 13% of all education levels. The remaining 1% is categorised as schools for students with disabilities (Sekolah Luar Biasa (SLB)). Details of the data composition are presented in Appendix 1, Table A1.1.

Our next important data are for the search intensity indicator. Previous literature has demonstrated that internet search provides wider access to information for students and impacts their ICT and general skills (Okyere, 2020). To construct this indicator, we utilised data from Google Trends to gather information on how many searches have been done on a specific keyword in a certain time interval. We selected 10 potential keywords related to online learning during the pandemic, consisting of both private and state-managed online learning platforms and self-learning related keywords, such as mathematical exercises. For example, the Government of Indonesia launched a programme that provides educational content to help students learning from home that aired on the state-owned television channel, Rumah Belajar.[8] Additionally, other education-related platforms, such as Zenius and Ruangguru announced support for Indonesian students learning during the pandemic by providing free educational content.[9] We included these topics in our potential keywords, and identified that the most

[8] https://www.kemdikbud.go.id/main/blog/2020/04/kemendikbud-hadirkan-program-tayangan-belajar-dari-rumah-di-tvri

[9] https://www.cnbcindonesia.com/tech/20200324111459-37-147189/dukung-belajar-di-rumah-zenius-gratiskan-80000-konten
https://www.kompas.com/edu/read/2020/08/04/115616571/tahun-ajaran-baru-ruangguru-lanjutkan-program-gratis-ini-tautannya?page=all
https://edukasi.kompas.com/read/2020/03/18/204829771/belajar-dari-rumah-quipper-beri-akses-gratis-lebih-dari-10000-video-dan

searched keywords are ‘Google Classroom’, ‘Rumah belajar’, ‘Quipper’, ‘soal matematika’, ‘ruang guru’, and ‘zenius’. Although there are plethora of other related keywords, we find that adding additional keywords only provided us with little additional information as the search frequencies were much lower than for the selected six keywords, as can be seen in Appendix 3.

Google Trends does not allow us to collect the raw number of searches for a specific time. Instead, we are provided with a search intensity relative to the highest searches for a maximum of five keywords in several periods. The data are also provided weekly. Ultimately, this indicator is sufficient to capture the dynamics before and after the COVID-19 pandemic at the provincial level. We therefore collected the data from 21 February 2016 to 24 January 2021 and obtained 260 weeks of observation for all 34 provinces to obtain 8,840 observation points in total. Lastly, we also used the 2019 Indonesian Socioeconomic Survey (Susenas) to obtain information on the socio-economic characteristics in the region.

3.2. Estimation method

Panel estimation/event study for online learning effectiveness

In this study, to analyse distance learning effectiveness, we use the search intensity indicator to approximate the distance learning effectiveness. Following Bacher-Hicks, Goodman, and Mulhern (2021), the search intensity is constructed as:

$$Search\ Intensity_{rt} = \sum_{i} \frac{\text{Total Google search numbers of keyword } i_{rt}}{\text{Total Google search numbers}_{rt}}$$

Where r represents the region at the province level. The total Google search numbers of keyword i over the maximum total google search numbers in region r and between all period $t \in T$ are obtained directly from Google Trends. Keyword i is an element of the set of keywords that are related to distance learning, as mentioned previously in the data part. As stated above, we choose six keywords that we can categorise into two groups. The first group of keywords consists of ‘Google Classroom’, ‘Quipper’, and ‘Rumah Belajar’ as a group of online learning tools. Meanwhile, the second group of keywords consists of ‘soal matematika’, ‘Ruang guru’, and ‘zenius’ as a group of online self-learning platforms. Since Google Trends provides data relative to the highest value for a specific trend, region, and keywords, we normalise the search intensity of all keywords using the search intensity in Indonesia, or, more specifically, the search intensity of all keywords is normalised relative to the search intensity of ‘Google Classroom’ in Indonesia since it contains the highest search intensity.

We demarcate the pre-COVID-19 period as the period before 16 March 2020 and the post-COVID-19 period as that after 16 March 2020. Although there were significant differences in the large-scale social restriction (PSBB) implementation times between regencies, distance learning was universally started from 16 March 2020 in all areas in Indonesia. Therefore, we universally use this demarcation period for all provinces. The universal trend is also shown by the average Google Trends period as shown later in the descriptive analysis.

For our event study, the first estimation is to observe the changes in search intensity between the pre- and post-COVID-19 periods. Our first event study is estimated as follows:

$$\ln(Search\ Intensity_{rt}) = \sum_{t=-26}^{-1} \beta_t Before_t + \sum_{t=1}^{26} \beta_t After_t + \alpha_1 PriorYears_t + \mu_{w(t)} + \lambda_{y(t)} + \epsilon_t$$

Second, we observe the changes in search intensity given the regional per capita expenditure group difference by interacting the regional income group with the pre-and post-COVID-19 indicators. Our second event study estimation is as follows:

$$
\begin{aligned}
&\ln(Search\ Intensity_{rt}) \\
&\quad = \sum_{t=-26}^{-1} (\beta_t Before_t + \gamma_t Before_t \times High\ PerCapitaGDRP_r) \\
&\quad + \sum_{t=1}^{26} (\beta_t After_t + \gamma_t After_t \times Low\ PerCapitaGDRP_r) \\
&\quad + \alpha_1 PriorYears_t + \alpha_2 PriorYears_t \times High\ PerCapitaGDRP_r \\
&\quad + \mu_{w(t)} + \lambda_{y(t)} + \epsilon_t
\end{aligned}
$$

where r is an indicator for the province, and t is an indicator for the week. $Before_t$ is a dummy variable that equals 1 if the observation is before 16 March 2020 within the same year, and $After_t$ is a dummy for observations after 16 March 2020. We exclude observations outside the academic year, that is from week 3 and 4 of December, week 1 of January, and week 2 and week 3 of July. $PriorYears_t$ is a dummy variable for the previous COVID-19 years, whilst $w(t)$ and $y(t)$, respectively, are week and year fixed effects. Our classification of per capita regional GDP is based on 2018 data, where we take provinces above the median as the high per capita regional GDP group and provinces below the median as the low per capita regional GDP group. With this specification, we can interpret coefficients β_t as differences or deviations in search intensity from the usual trends in previous years in the same weeks.

Second, we estimate the search intensity using a difference-in-difference method by accounting for the differences pre- and post-COVID-19 for regions with the high per capita gross domestic regional product (GDRP) group and the low per capita GDRP group. The specification is as follows:

$$
\begin{aligned}
&\ln(Search\ Intensity_{rt}) \\
&\quad = \beta_1 PostCovid_t \times High\ PerCapitaGDRP_r \\
&\quad + \beta_2 PostCovid_t \times Low\ PerCapitaGDRP_r \\
&\quad + \sigma High\ PercapitaGDRP_r + \mu_{w(t)} + \lambda_{y(t)} + \epsilon_t
\end{aligned}
$$

Coefficients β_1 and β_2 measure the post-COVID-19 changes in skill intensity for high or low regional per capita GDP groups. Then, we compute the difference between the coefficients to find the net effect of COVID-19. We also estimate using regional per capita GDP as a continuous variable and other continuous variables, such as household and school internet access in the province, and the Gini coefficient.

4. Analysis and results

4.1. Descriptive analysis

Summary of schools' adoption of online learning

Although distance learning measures have been issued since 16 March 2020, the adoption of online learning has been widely diverse between provinces. According to a school survey by the Ministry of Education (see Table 1), only 87.38% of responding samples had already adopted online learning, whilst the rest were still in classroom/offline learning. The low adoption is widely pronounced in schools in less-developed provinces, such as Aceh (55.28%), Bangka Belitung (58.53%), and West Papua (76,77%). This fact also suggests that most schools rarely invest in their digital infrastructure to accommodate online learning, even though distance learning is mandatory by law, as online learning adoption seems to be lacking in provinces with low digital connectivity. This information is also supported by the fact that the Ministry of Education and Cultural Affairs (MoRA) with the revision of MoRA's Ministerial Decree (Peraturan Menteri Pendidikan) number 8 year 2020 to MoRA's Ministerial Decree number 19 year 2020 provided the instruction for the use of School Operational Grants (Bantuan Operational Sekolah (BOS)) during COVID-19 to be reallocated for health protocol measures, teachers' and students' internet quotas, and phone credits.[10] There is no indication that BOS is allocated to improve hard digital infrastructure.

Our early observation from this data creates a link between learning effectiveness and regional development. Therefore, our next step explores the regional disparity in terms of school and learning quality and digital infrastructure.

[10] https://djpb.kemenkeu.go.id/portal/id/berita/berita/berita-nasional/3361-selama-pandemi-covid-19,-dana-bos-dapat-juga-digunakan-untuk-membiayai-penyediaan-sarana-protokol-kesehatan,-untuk-pembelian-kuota-data,-dan-pulsa.html

Table 1. Number of Schools by the Adoption of Learning Types (August 2020)

No.	Province	Online learning		Offline learning	
		Total	**%**	**Total**	**%**
1	Prov. D.K.I. Jakarta	2,300	99.35	15	0.65
2	Prov. Jawa Barat	12,603	92.66	999	7.34
3	Prov. Jawa Tengah	11,172	91.41	1,050	8.59
4	Prov. D.I. Yogyakarta	2,084	98.96	22	1.04
5	Prov. Jawa Timur	13,723	88.25	1,828	11.75
6	Prov. Aceh	1,068	55.28	864	44.72
7	Prov. Sumatera Utara	3,375	89.31	404	10.69
8	Prov. Sumatera Barat	990	85.64	166	14.36
9	Prov. Riau	1,385	87.11	205	12.89
10	Prov. Jambi	1,015	66.95	501	33.05
11	Prov. Sumatera Selatan	1,841	78.84	494	21.16
12	Prov. Lampung	2,023	78.78	545	21.22
13	Prov. Kalimantan Barat	1,492	91.82	133	8.18
14	Prov. Kalimantan Tengah	994	86.81	151	13.19
15	Prov. Kalimantan Selatan	2,107	96.96	66	3.04
16	Prov. Kalimantan Timur	1,070	97.72	25	2.28
17	Prov. Sulawesi Utara	539	93.09	40	6.91
18	Prov. Sulawesi Tengah	692	89.41	82	10.59
19	Prov. Sulawesi Selatan	2,538	88.80	320	11.20
20	Prov. Sulawesi Tenggara	458	75.45	149	24.55
21	Prov. Maluku	311	71.82	122	28.18
22	Prov. Bali	2,209	98.84	26	1.16
23	Prov. Nusa Tenggara Barat	1,777	82.34	381	17.66
24	Prov. Nusa Tenggara Timur	1,117	58.48	793	41.52
25	Prov. Papua	334	57.99	242	42.01
26	Prov. Bengkulu	595	81.40	136	18.60
27	Prov. Maluku Utara	178	64.26	99	35.74
28	Prov. Banten	2,056	80.16	509	19.84
29	Prov. Kepulauan Bangka Belitung	199	58.53	141	41.47
30	Prov. Gorontalo	442	98.44	7	1.56
31	Prov. Kepulauan Riau	762	90.28	82	9.72
32	Prov. Papua Barat	195	76.77	59	23.23
33	Prov. Sulawesi Barat	414	91.39	39	8.61
34	Prov. Kalimantan Utara	157	90.23	17	9.77
Total	**Grand total**	**74,225**	**87.38**	**10,724**	**12.62**

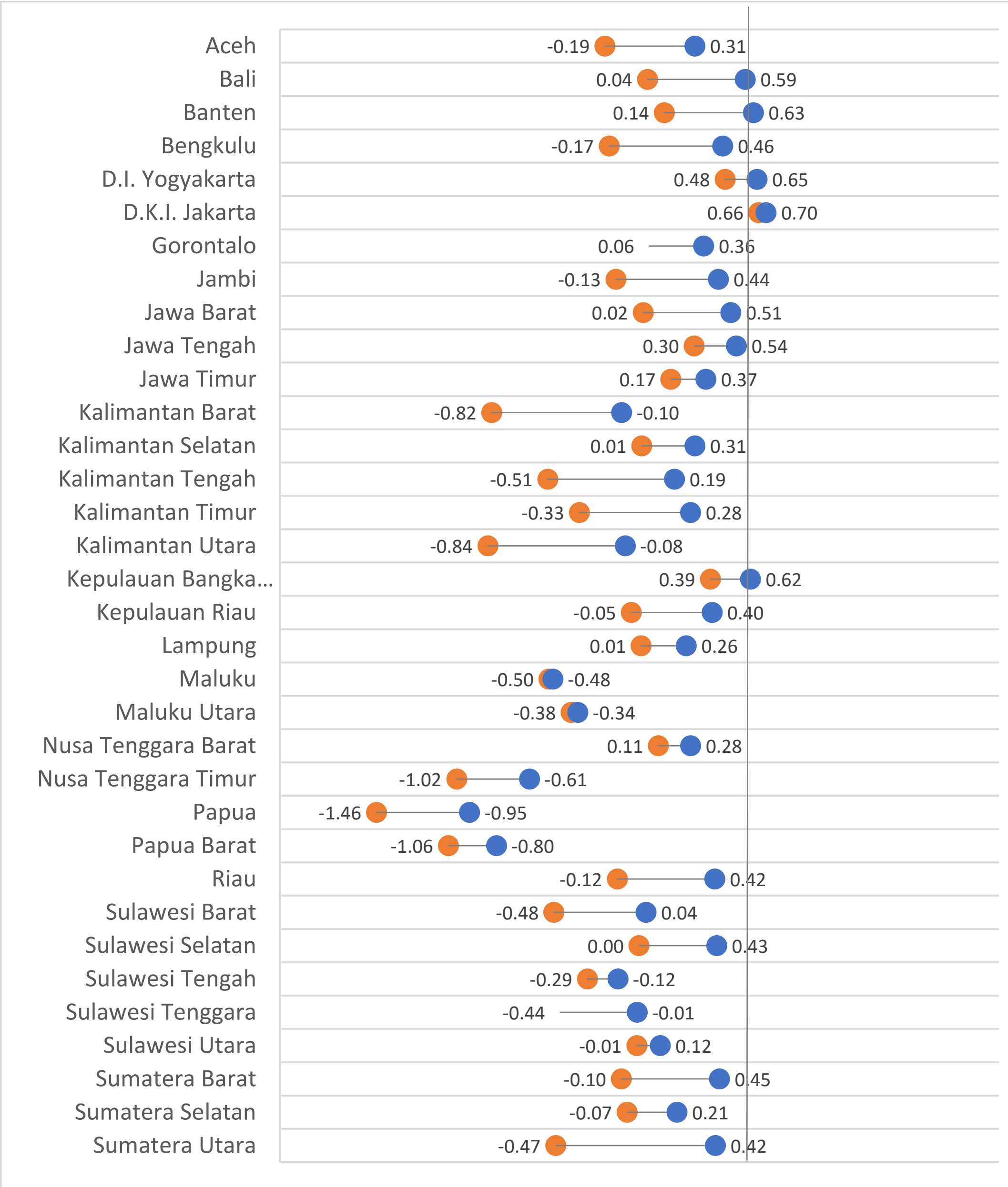
Source: Dashboard Kesiapan Belajar Kemendikbud (2020).

A deeper look at schools' quality dispersion

We continue our analysis of Dapodik data by looking at infrastructure access and quality. In term of access, 97% of schools in Indonesia are connected with electricity, with 89% through the national electricity company (Perusahaan Listrik Negara (PLN)). However, this progress is hampered by the digital divide in unequal internet connectivity in Indonesian schools. A share of 45% of schools have no internet connection, whilst 55% of schools have access to the internet. Nevertheless, schools that are connected to the internet are still concentrated in Java and Sumatera, with Jakarta having the highest percentage of internet access at around 73%, whilst Maluku has the lowest percentage of internet access at 27%.

As our school data contains a lot of information, we try to condense the information into several parts. First, we constructed an index to capture school quality in the manner explained in Appendix 1. The summary of the index by province is displayed in Figure 1 below.

Figure 1. Public versus Private School Average School Quality Index by Province



Notes: Orange is the public school average index and blue is the private school average index. Since the data is normalised, 0 is the national average index. In addition, the index is also normalised by 1 standard deviation. Therefore, scores with more than 1 or -1 are above or below 1 standard deviation.
Source: Data are from https://dapo.kemdikbud.go.id/, authors' calculation.

As shown in Figure 1, there is a stark difference in school quality across regions by type of ownership. Public schools unequivocally have both lower infrastructure quality and teaching capability across regions. In addition, the western part of Indonesia, especially the provinces in Java, has significantly higher quality than the eastern part, such as Papua, West Papua, and East Nusa Tenggara. The highest average index scores for public and private schools are in Jakarta, with scores of 0.66 and 0.70, respectively, whilst the lowest average index scores for public and private schools are in Papua, with scores of -1.46 and -0.95, respectively. Also, North Kalimantan and West Kalimantan have the largest gap between public and private schools, with a gap of more than 0.7.

Looking at more specific variables in Table 2, the differences between public and private schools and the inequality between eastern and western Indonesia provinces are more glaring. Schools' internet availability is highly varied across provinces, with the lowest in public schools in Papua province where only 18% of schools have access to the internet, whilst the highest is in public schools in DKI Jakarta (84%), followed by private schools in South Sumatera (67%), public schools in Banten and West Java, and private schools in DKI Jakarta and West Java (66%). There is also an indication that public schools are not equally well equipped with internet access across provinces, whilst private schools are more equally well equipped with internet access across provinces.

Table 2. Comparison Between School Quality Indicators by Province and School Ownership Type

Province	Internet availability (% of schools)		Student/Teacher ratio		Student/Classroom ratio	
	Public	**Private**	**Public**	**Private**	**Public**	**Private**
Prov. Aceh	56%	62%	7.0	6.3	14.3	12.7
Prov. Bali	53%	56%	13.1	9.9	18.7	15.7
Prov. Banten	66%	65%	19.0	12.1	26.6	17.1
Prov. Bengkulu	45%	49%	10.1	8.2	15.7	13.2
Prov. D.I. Yogyakarta	62%	61%	12.7	8.0	17.9	11.5
Prov. D.K.I. Jakarta	84%	66%	15.3	11.2	13.2	15.4
Prov. Gorontalo	43%	61%	11.6	8.2	15.8	16.2
Prov. Jambi	54%	61%	10.2	9.0	16.0	13.2
Prov. Jawa Barat	66%	66%	19.4	11.8	25.6	17.7
Prov. Jawa Tengah	60%	61%	14.7	9.9	18.6	14.7
Prov. Jawa Timur	57%	61%	11.4	9.3	15.4	14.4
Prov. Kalimantan Barat	34%	48%	12.5	11.3	14.8	16.8
Prov. Kalimantan Selatan	52%	56%	9.4	9.5	12.9	15.1
Prov. Kalimantan Tengah	36%	50%	7.8	10.0	10.3	15.5
Prov. Kalimantan Timur	49%	58%	11.6	10.9	17.1	14.5
Prov. Kalimantan Utara	33%	57%	7.4	9.6	12.6	15.6
Prov. Kepulauan Bangka Belitung	58%	62%	15.6	12.4	20.6	18.3
Prov. Kepulauan Riau	53%	61%	8.6	8.4	15.1	12.6
Prov. Lampung	58%	63%	12.3	9.2	19.0	14.7
Prov. Maluku	29%	23%	11.0	12.3	16.2	15.3
Prov. Maluku Utara	35%	39%	11.3	9.9	14.7	15.1
Prov. Nusa Tenggara Barat	63%	65%	9.9	6.9	19.0	15.0
Prov. Nusa Tenggara Timur	47%	52%	11.0	12.8	16.2	17.2
Prov. Papua	18%	27%	16.6	16.6	18.8	18.6
Prov. Papua Barat	26%	30%	11.4	12.7	13.2	14.5
Prov. Riau	57%	64%	11.7	9.9	18.3	15.5
Prov. Sulawesi Barat	33%	45%	9.2	9.0	13.5	13.6
Prov. Sulawesi Selatan	54%	62%	10.4	9.2	15.8	13.1
Prov. Sulawesi Tengah	36%	43%	10.1	8.9	13.8	12.2
Prov. Sulawesi Tenggara	42%	52%	10.2	6.8	15.0	9.7
Prov. Sulawesi Utara	47%	46%	9.2	10.9	11.9	11.3
Prov. Sumatera Barat	53%	61%	11.5	7.7	16.9	10.7
Prov. Sumatera Selatan	61%	67%	12.6	10.8	21.0	16.2
Prov. Sumatera Utara	50%	62%	12.7	12.6	17.8	17.1
National	**54%**	**59%**	**12.1**	**10.4**	**17.1**	**15.3**

Note: Percentages are based on the number of public or private schools, respectively, in the region.
Source: Data are from https://dapo.kemdikbud.go.id/, authors' calculation.

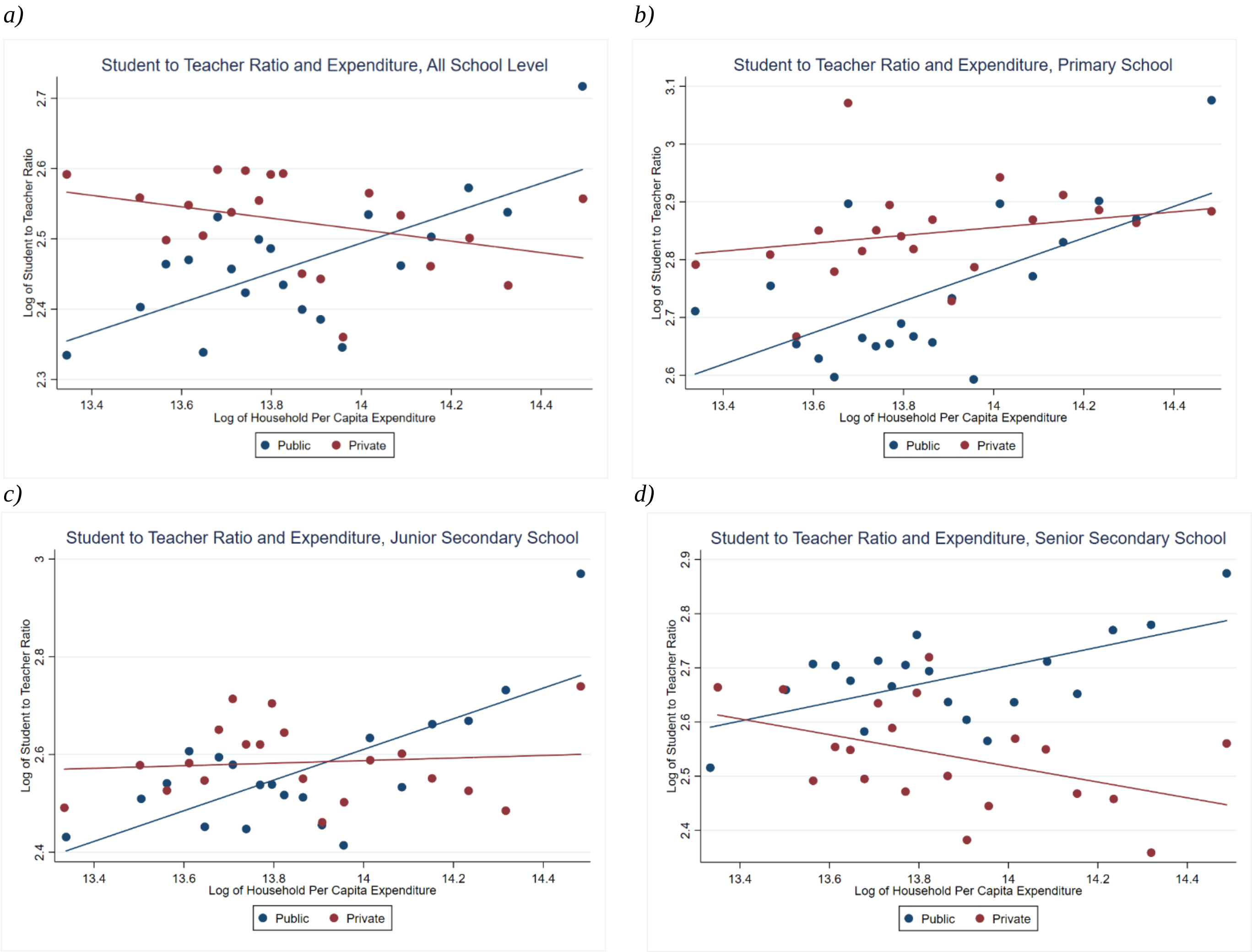
On the other hand, student/teacher and student/classroom ratios seem to have mirroring distributions with school quality. Densely populated and more developed provinces, such as Java and Sumatera, have relatively higher student/teacher and student/classroom ratios. In addition, public schools relatively have higher scores for both ratios as they provide free tuition costs and cover a larger scope of the population.

Preliminary evidence of differences in school access depending on households' socio-economic status

Figure 2 illustrates the relationship between the student–teacher ratio and household per capita expenditure in the corresponding regions. The plot shows a pronounced gap between the capacity of public and private schools.

Generally, the relationship between the student–teacher ratio and wealth is contradictory between public and private schools (1a). This difference is particularly palpable at the higher-secondary level as regions with higher average household wealth are associated with a lower student-to-teacher ratio for private education (1d). However, for public schools, household wealth does not seem to warrant a better teaching capacity as there is a positive association between household per capita expenditure and the student-to-teacher ratio. These findings show that teachers in public schools are responsible for leading the learning processes for large student bodies, despite the schools being located in relatively richer districts. However, the difference between public and private schools seems to be relatively subtle at the primary and junior-secondary level, possibly due to an already large number of students in this group.

Figure 2. Gaps in the Student-to-Teacher Ratio between Public and Private Schools



Source: Dapodik and Susenas (2019); authors' calculations.

Internet access is unequal even between schools and households

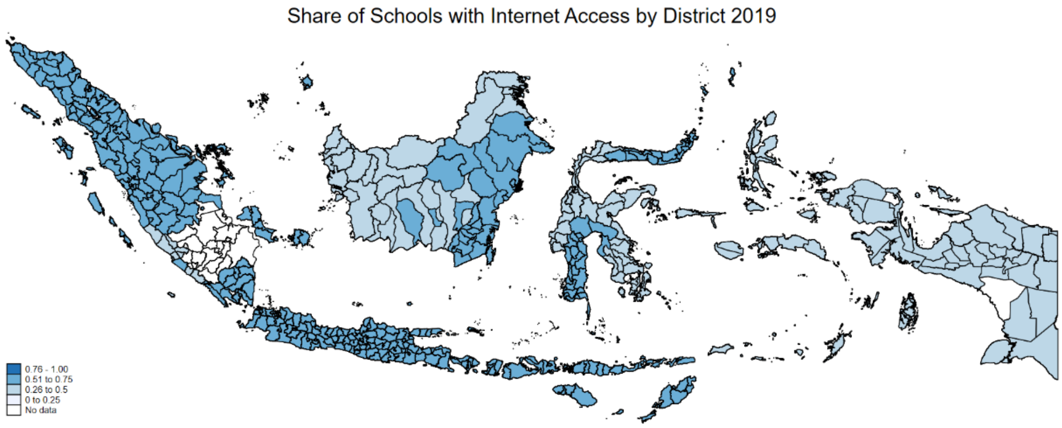
Internet access is one of the most important components that affect the quality of distance learning. In Indonesia's case, both households' and schools' internet access play prominent roles in contributing to learning quality. Household internet access enables both students and teachers to create and access online teaching materials. Meanwhile, internet access in schools has helped teachers to prepare and support online teaching materials even before the pandemic.

School infrastructure capacity in terms of school access to the internet shows an expected pattern as illustrated by Figure 2. The map shows that most districts in Java as well as some parts of Sumatera have almost up to 75% of their schools of all education levels connected to internet, with region like Jabodetabek with more than 75% of their school connected to internet. Meanwhile, the eastern region, particularly Papua, has a lower share of internet infrastructure, with less than 50% of schools having access to the internet.

In comparison, internet access at the household level also differs greatly by region (Figure 3). Cities and district in Java and Sumatra mainly have up to 75% of their households connected to internet. Meanwhile, regions in the eastern part of Indonesia have less than 25% of their households connected to the internet. This fact makes distance learning even harder and aggravates the education gap between Java and other regions. During the pre-pandemic period, students in the eastern part of Indonesia who could not connect to internet in their houses could still access this digital infrastructure at school. With schools closed, not only do students lose access to these facilities but they also have hindered learning progress due to their inability to access the internet.

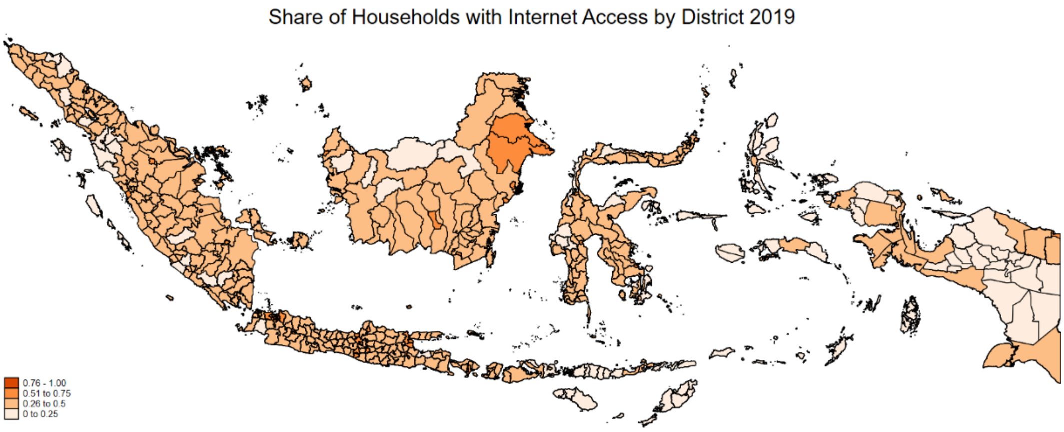
Interestingly, more schools seem to be provided with better internet access in several areas, such as Java, North and West Sumatera, East Kalimantan, and South Maluku, whilst household internet access limitations are more evenly spread across Indonesia. This suggests that regional inequality in terms of schools' quality is more pronounced than the inequality in household internet access. However, it should be noted that in general, internet access is still lacking even amongst more developed regions, which will become an impediment for the distance learning process.

Figure 3. Map of School Internet Infrastructure by District, 2019



Source: Data are from https://dapo.kemdikbud.go.id/; authors' calculations.

Figure 4. Map of Household Internet Access by District, 2019

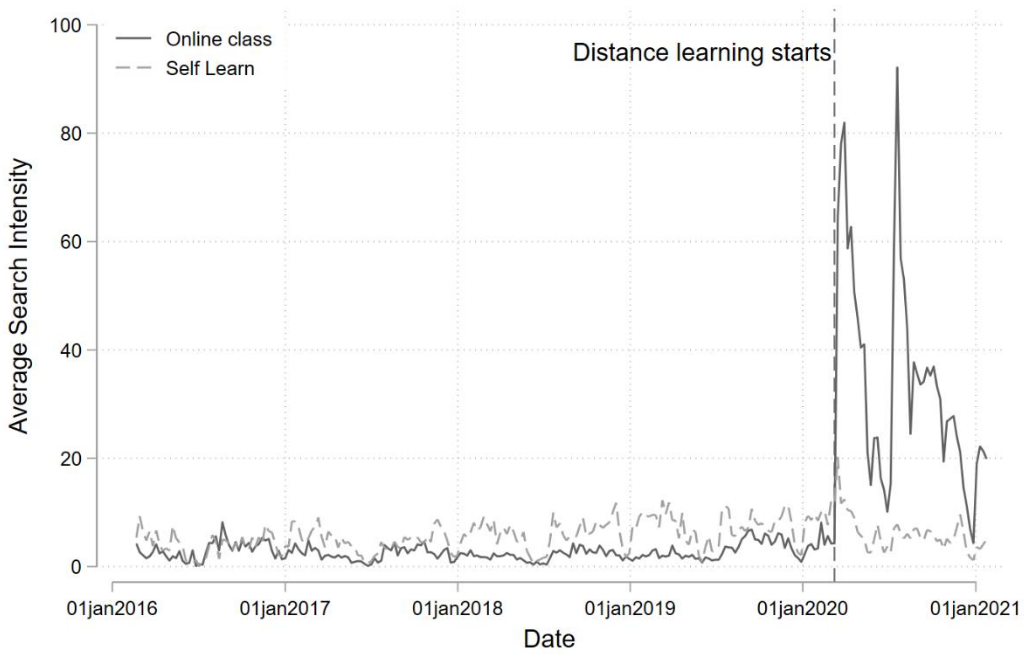


Source: Susenas (2019); authors' calculations.

Google search intensity

With learning activities going fully online during the pandemic, there is an evident difference in search intensity relative to the pre-COVID-19 period. As previously mentioned, we mark the timeline cut-off that divides the pre-pandemic and pandemic trends at 16 March 2020. Figure 5 reports that the Google trends of keywords related to online class activity rapidly increase once distance learning started, by almost 80 times higher relative to the pre-pandemic timeline.

Figure 5. Search Intensity Trends

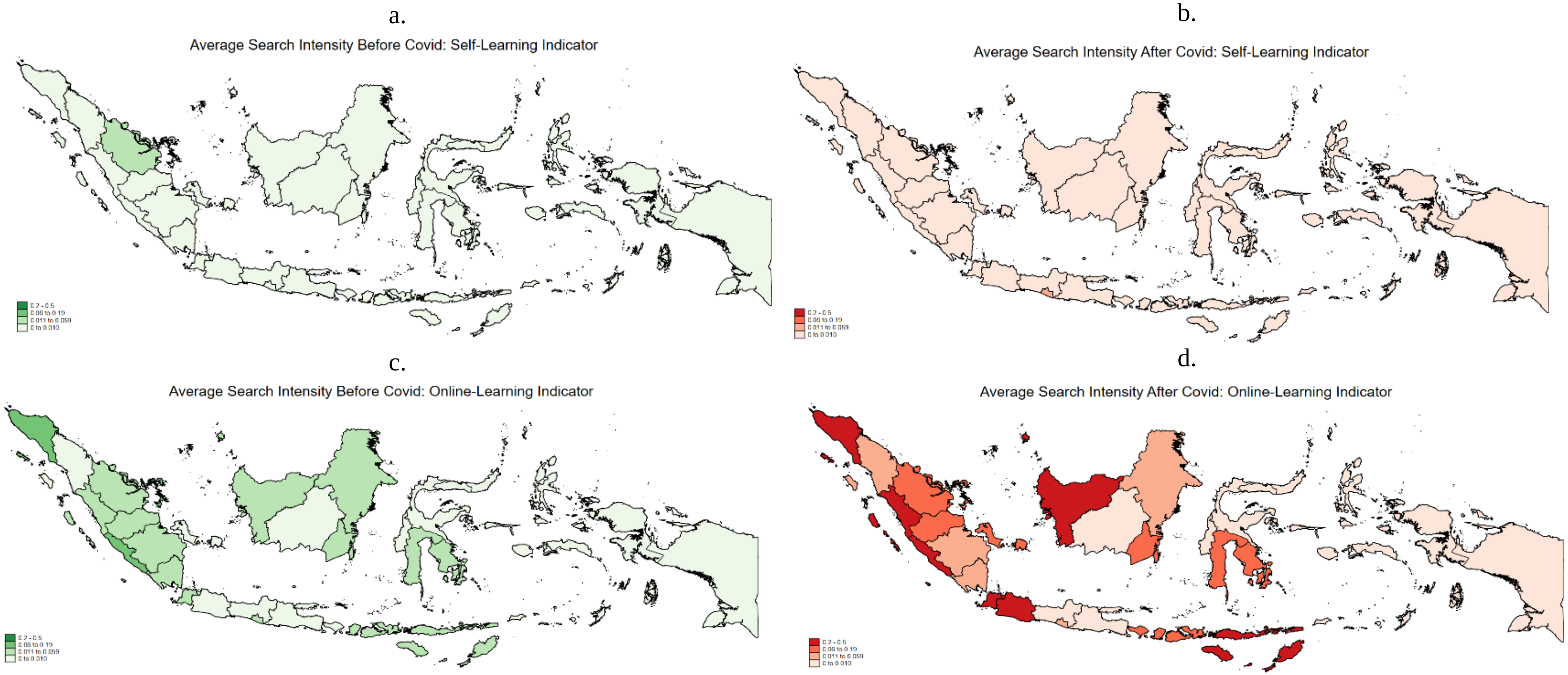


Source: Google Trends.

If we examine the search intensity for online-learning related keywords across provinces (Figures 6c and 6d), the increasing trend is mostly consistent for all regions, with provinces with low internet users in the eastern part maintaining a low number for the search intensity despite the pandemic. Some regions in Sumatera experienced a striking increase in online-learning search intensity. However, the search intensity for self-learning related keywords does not follow the same pattern, and this is consistent for both national and regional trends if we compare Figure 5 and Figures 6a and 6b. The average search intensity for these keywords was already low even before the pandemic, and behaviour changes did not take place during the distance learning period.

This case could possibly be explained by two things. First, it is probable that during distance learning, students only rely on teacher-oriented materials to continue their learning process. Hence, there is little evidence to show that students have also been utilising other sources to enrich their learning process independently. Second, looking at the bigger picture, this issue is possibly related to the digital infrastructure gap. As reported in Susenas 2019, most Indonesian internet users access online information through smartphones, and only 13% of Indonesians have access to personal computers. Different devices are associated with different uses of internet activity. As suggested by Ghose, Goldfarb, and Han (2011) internet browsing activity using mobile phones imposes a higher search cost that restricts utilisation of their devices. In addition, there is little difference in search intensity between regions, as shown in Appendix 4. However, self-learning search intensity is found to be higher in the less-developed regions. This suggests that students in less-developed regions still need to independently learn to offset their lack of classroom teaching quality.

Figure 6. Average Search Intensity by Province



Source: Google Trends.

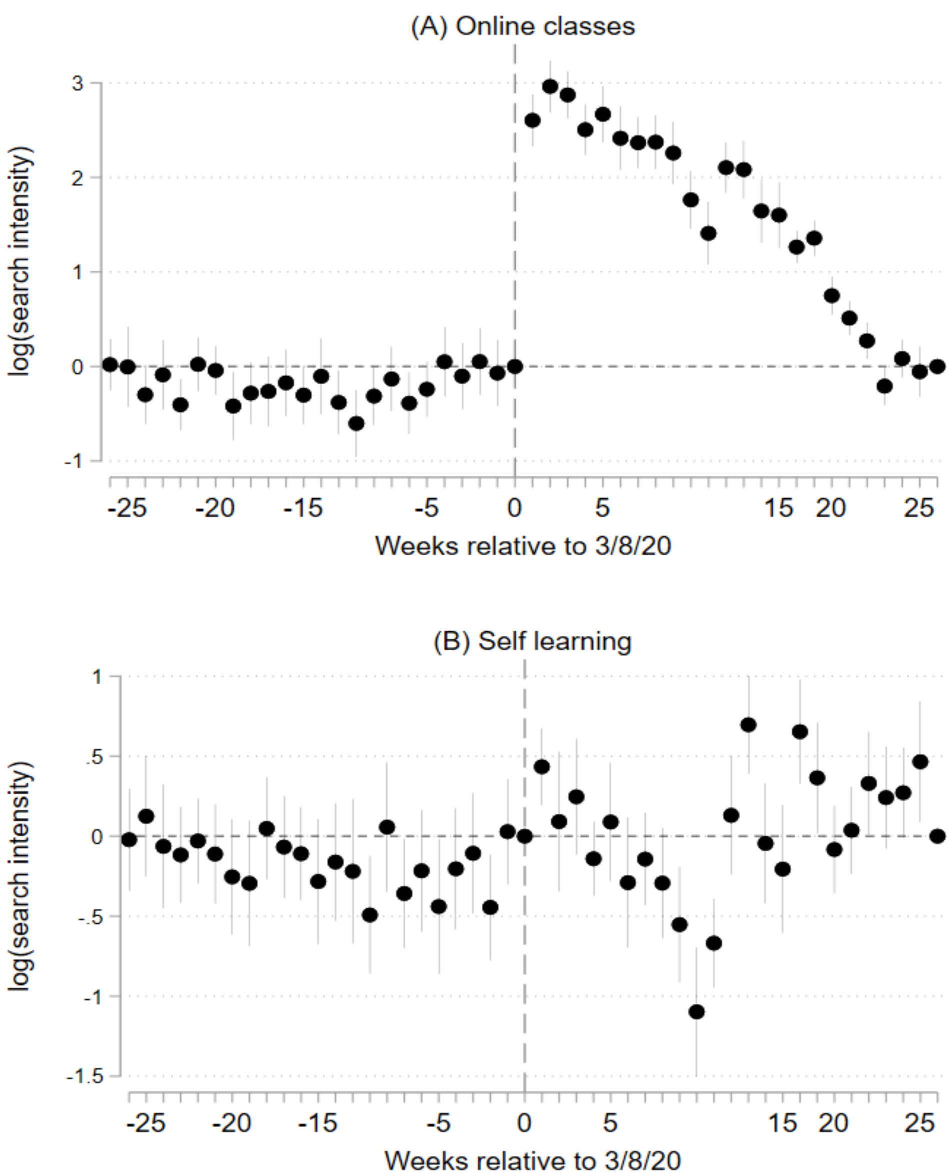
4.2. Estimation results

We begin this section with the first event study specification by estimating the changes in search intensity given the post-COVID-19 trends without interacting any variables. We intend to observe whether the COVID-19 pandemic has significantly changed the usual weekly patterns of search intensity in accessing online class platforms or conducting self-learning activities using the internet. As we can see from Figure 6, school closures after 8 March 2020 due to pandemic significantly affected the search intensity patterns for online classes, where the weekly coefficients are significantly higher after school closures, with the highest increases within three weeks just after the closures. However, the pandemic's effect on changes in search intensity gradually decrease over time, and the search intensity is not affected much by the pandemic 23 weeks after the school closures. There are two possible explanations for this result. First, students and parents alike might already have become accustomed in using online classroom platforms and choosing their own platforms without the need to do a Google search, as stated by Bacher-Hicks, Goodman, and Mulhern (2021) in explaining a similar pattern in the US. Second, another possible reason, especially in Indonesia's case, is that learning activities gradually decrease over time after the pandemic. This has been evident in several surveys where children do not continue school due to their parents' socio-economic conditions or due to online learning activities that are deemed ineffective by their parents (Alifia et al., 2020).

Interestingly, school closures do not affect changes in self-learning search intensity as much as online class search intensity. First of all, the magnitude of the post school closures week coefficient is noticeably lower, nearing zero magnitude, than for online class search intensity changes, ranging from around -1.2 to 0.7. Second, the estimation results for the post school closures weekly coefficients are generally not robust. Slight changes in the pattern can be seen after the school closures, where the coefficient for 1 week after the pandemic positively affects the change in self-learning search intensity. However, the magnitude decreases over time until week 11 after the pandemic. Then, the search intensity pattern is back to its usual pattern. This result suggests that distance learning induced by the pandemic neither encourages students to self-learn using the internet nor encourages parents to assist their children. This might imply further learning losses as this reduces the effectiveness of distance learning and online classrooms generally must be assisted by self-learning.

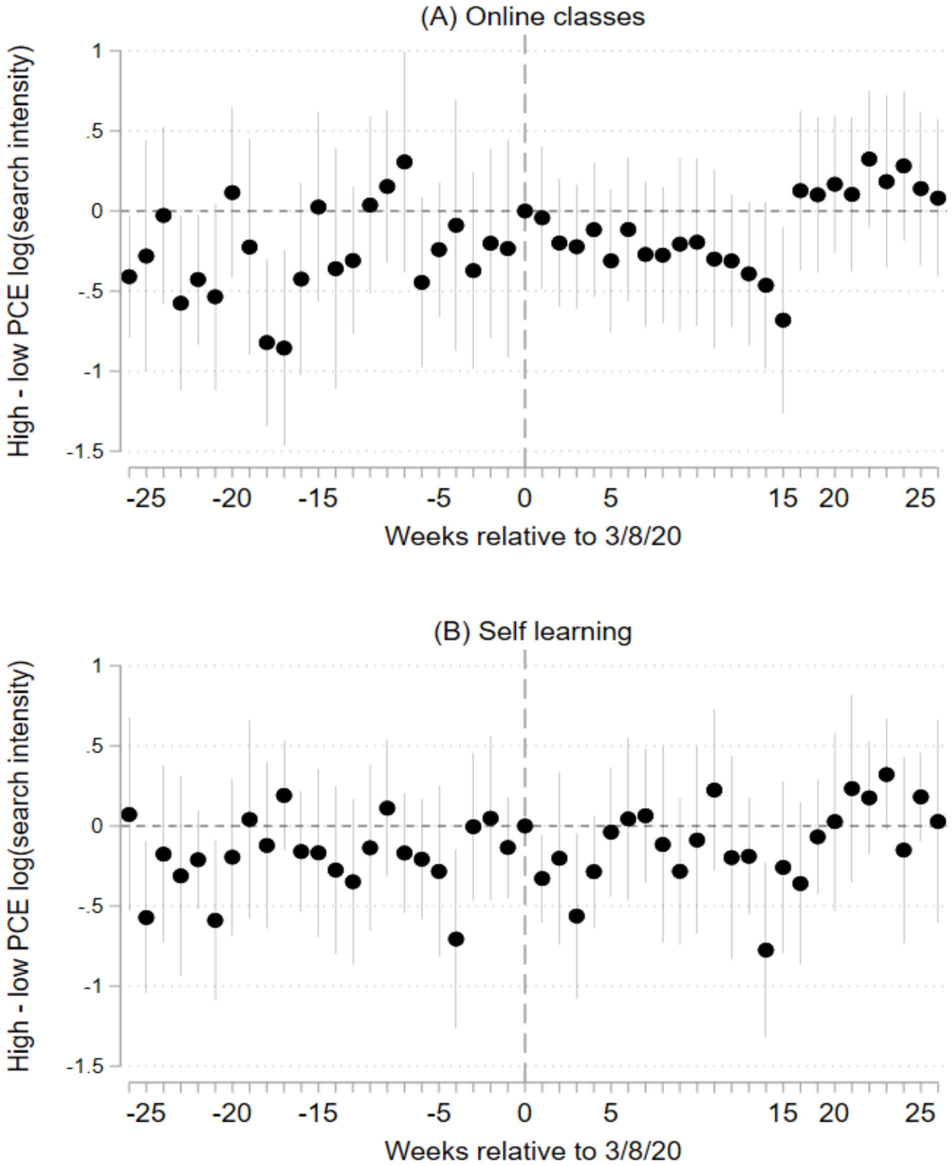
From our second estimation, we intend to observe whether there is difference between high and low per capita expenditure in affecting the search intensity pattern. From Figure 7, we find that there is no distinct difference between the two groups. This evidence suggests that there is little to no inequality between the high and low socio-economic groups in terms of learning engagement. This is contrary to our prior, where higher per capita expenditure, which reflects higher income and socio-economic status overall, posits higher online learning engagement since they are more adept at using digital platforms, have higher access to digital infrastructure, have more knowledge, and generally have more access and other resources. One explanation for our result that only few students in Indonesia utilised online learning platforms in the first place regardless of the region. Thus, the search intensity for online class keywords does not differ between groups even though it rises significantly after the school closures, whilst there is no significant increase in the self-learning search intensity pattern in the first place. In addition, there is also no significant difference between the low and high per capita expenditure groups in the case of changes in the self-learning search intensity. This result also further emphasises the fact that school closures do not encourage self-learning activities using online platforms, even in regions with a higher socio-economic status.

Figure 7. Coefficient Plot from the Event Study Estimation Without Interaction Terms



Source: Authors' calculations.

Figure 8. Coefficient Plot from the Event Study Estimation with Interaction Terms



Source: Authors' calculations.

As for our panel and difference-in-difference estimations, we try to observe the changes in online classroom and self-learning search intensity with regards to several socio-economic indicators, particularly per capita expenditure, the Gini coefficient, rural population share, school quality index, parents' education level, and technology access, which are internet, computer, and cell phone access. As stated above, we focus on the differences between high and low per capita expenditure region groups to capture whether there are any differences between learning engagement between those groups given our prior that regions with higher socio-economic status have greater access to knowledge and digital infrastructure, thus creating inequality in online learning engagement. We also place specific attention on the search intensity for 'Google Classroom' keywords, as Google Classroom is the most used platform for online classrooms.

First, our estimation results (as described in Table 2) show that the changes in search intensity for online classrooms, including Google Classroom, significantly increased after the school closures by 1070% (246 log points), but had little to zero magnitude in affecting changes in the search intensity of self-learning related keywords, at only a 2.9% decrease (-3 log points). This result is consistent with our event study estimation, where the pattern of online classroom related search intensity increases significantly after school closures, whilst the pattern for self-learning related search intensity has little change overall.

Second, we look at the difference-in-difference estimation by comparing between high and low per capita expenditure region groups as an indicator of socio-economic status difference. It is evident that both per capita expenditure groups have a statistically significant increase in online classroom related search intensity after the school closures, where the high per capita expenditure region group has a 1143% (252 log points) increase, the and low per capita expenditure region group has a 991% (239 log points) increase. These increases hold true for Google Classroom as the most used platform. Thus, the net difference between the two groups is relatively small, at around 15% (14 log points) with a statistically insignificant difference. Meanwhile, there are no significant changes in self-learning related search intensity between the pre- and post-school closures in both groups.

From this result, coupled with our previous result and the statistically insignificant result from interacting the school closures dummy with per capita expenditure as a continuous variable, strongly confirms that the difference in per capita expenditure does not affect learning engagement for both the online classroom and self-learning activities. It is also clear that regions with higher per capita expenditure do not have any significant advantage or difference in search intensity before the school closures, thus strengthening our previous argument that online learning engagement was already very low regardless of the per capita expenditure.

On the other hand, there are slight variations when we interact the post-COVID-19 dummy with technology proxies and other socio-economic conditions. Although with a weakly significant result, we learn that every 1 percentage point increase in the share of internet users in a province increases the online classroom related search intensity by around 0.35% to 2.03% (0.30–1.11 log points), whilst the effects of computer adoption and cell phone ownership magnitude are imprecisely estimated with a positive relation to the online class related search intensity.

Table 3. Changes in Search Intensity by Per Capita Expenditure, Technology, and Other Socio-Economic Measures

	(1)	(2)	(3)
	Online Classroom	Google Classroom	Self-learning
Post Covid	2.46^{***}	2.46^{***}	-0.03
	(0.05)	(0.06)	(0.03)
Post Covid * High Percap. Expenditure	2.52^{***}	2.53^{***}	-0.06
	(0.07)	(0.09)	(0.04)
Post Covid * Low Percap. Expenditure	2.39^{***}	2.39^{***}	-0.00
	(0.07)	(0.07)	(0.05)
High Percap. Expenditure	0.01	0.08	-0.14
	(0.09)	(0.08)	(0.09)
High-Low SES Change	0.14	0.14	-0.06

	(0.09)	(0.11)	(0.07)
Post Covid * ln Percapita Expenditure	0.38	0.36	-0.25*
	(0.25)	(0.28)	(0.13)
Post Covid * Share of internet user	0.71*	0.84	-0.87***
	(0.41)	(0.52)	(0.21)
Post Covid * Share of computer use	1.44	1.13	-1.99***
	(1.23)	(1.51)	(0.68)
Post Covid * Share of cell phones owned	0.61	0.96	-1.00***
	(0.62)	(0.80)	(0.31)
Post Covid * Gini coefficient	-2.05	-3.30**	-0.52
	(1.36)	(1.41)	(0.83)
Post Covid * Share of rural pop.	-0.50**	-0.52*	0.40***
	(0.23)	(0.27)	(0.12)
Post Covid * School quality index	0.08	0.12	-0.17**
	(0.10)	(0.12)	(0.07)
Post Covid * HH highest education	0.18	0.11	-0.12
	(0.17)	(0.22)	(0.11)
Observations	7,888	7,888	7,888

Notes: All dependent variables are in logarithmic scale. The standard errors in parenthesis are robustly estimated and clustered at the province level (* p < .10, ** p<.05, *** p<.01). Post Covid is a dummy for post-school closures on 16 March 2020. High and low per capita expenditure groups are divided based on the median. The share of internet users, computer use, cell phones owned, Gini coefficient, and share of rural population are scaled between 0 and 1. The school quality index is normalised with mean and 1 standard deviation; therefore, every 1 point change reflects changes in 1 standard deviation. All estimations include week fixed effects (1–52) and school year fixed effects (2016–2021). Observations exclude schools' long holidays (week 3 and 4 of December, week 1 of January, and week 2 and 3 of July).

Source: Authors' calculations.

Interestingly, greater technology access in a province seems to decrease self-learning related search intensity significantly. Every 1 percentage point increase in the share of internet users in the region lowers the search intensity by 0.58% (-0.87 log points), whilst every 1 percentage point increase in the share of computer adoption lowers the search intensity by 0.86 (-1.99 log points), and a 1 percentage point increase in the share of cell ownership of the total population in a province lowers it by 0.63% (-1 log points).

Whilst these results may seem inconsistent, there are two possible explanations. First, it might be that technology access creates more distraction for distance learning rather than encouraging students or parents to conduct more self-learning activities; thus, technology access reduces the self-learning related search intensity. This argument is supported by Dontre (2020), who states that academic distraction has become increasingly problematic in recent years due to social media multitasking, and this issue has been greatly exacerbated due to the COVID-19 pandemic and mandatory social distancing regulations. Second, it may be that provinces with a higher share of technology adoption are also accompanied by higher socio-economic status, school quality, and learning quality, therefore reducing the need for students to conduct self-learning activities and parents to assist them since they are content with the learning activities given by schools. On the contrary, provinces with lower technology adoption might imply lower learning and teaching quality, which pushes both students and parents towards self-learning activities. This argument is supported by the estimation result on school quality.

We then turn to the other socio-economic measures, particularly within-province inequality as represented by the provincial-level Gini coefficient and the share of the rural population, and school quality within provinces as proxied by the school quality index that we previously constructed. Whilst the Gini coefficient does not affect self-learning related search intensity, a higher Gini coefficient slightly decreases the Google Classroom search intensity by 0.96 (-3.30 log points) for every 0.01 point of increase in the Gini coefficient. Meanwhile, every 1 percentage point increase in the share of the rural population in provinces decreases the online classroom related search intensity by 0.39 (-0.50 log points) and increases the self-learning related search intensity by 0.49 (0.40 log points).

Lastly, consistent with our previous findings, 1 standard deviation increase in school quality index decreases the self-learning related search intensity by 15 (-17 log points). Meanwhile, there is no major effect from the difference in parents' level of education.

These results further strengthen our argument that within-province inequality contributes more to the disparity in online learning engagement. The share of rural population and school quality index further provide us with interesting results, where a greater rural population increases self-learning activities using the internet, whilst higher school quality lowers it. Consistent with our previous argument, this result suggests that regions with lower access to quality education and technology force both students and parents to complement school learning materials through self-learning activities. Eventually, the self-learning necessity for students in these regions becomes more important during the school closures period.

To summarise our findings, we have strong evidence that the sudden jump in online learning engagement is due to COVID-19's school closures, but only in online classroom related keywords and not in self-learning related keywords, denoting the lack of active participation from students and parents alike to offset the potential decrease in learning quality from the online classes given by schools. However, contrary to our hypothesis, there is no evidence that the differences in per capita expenditure between provinces cause wider gaps in online learning engagement. However, that does not necessarily mean inequality does not widen the gap between online learning engagement. Instead, we find that within-province inequality, as reflected by the provincial Gini coefficient and the share of the rural population in provinces, widens the gap in online classroom engagement by a relatively large margin. In addition, to overcome the online learning inadequacy in less-developed areas, particularly in rural areas, students are forced to initiate their self-learning activities using online platforms. This fact is further reinforced by our results that higher school quality and higher technology access actually lower self-learning related search intensity. Lastly, there is an indication that higher technology access creates more academic distraction rather than enhancing online learning engagement due to the fact that it reduces self-learning search intensity.

5. Conclusion and policy implications

5.1. Conclusion

This study provides a timely assessment of Indonesia's current new-normal framework as the government is currently implementing distance learning whilst also planning limited capacity classroom scenarios to address the possible learning losses. Whilst the government intends to combine both scenarios based on regional conditions, a lack of tools and proper analysis could potentially hinder them in deciding which regions are most suited for either scenario, and what needs to be improved in order to reduce potential learning losses. First, we provide evidence to measure the distance learning effectiveness through online learning engagement and identify the socio-economic conditions that can exacerbate the gaps in online education attainment. Second, we provide information and analysis to identify which regions and schools are lacking both physical and digital infrastructure by constructing the school quality index. Our study could provide significant improvements to the policy targeting framework in both distance learning and school reopening scenarios.

Our findings from the descriptive analysis show that school quality is indeed unequal across regions. First, using our constructed school quality index, we find that school quality is higher in western Indonesian provinces as they are more developed. Public schools generally also have lower quality relative to private schools, except in Jakarta. Interestingly, more-developed provinces have higher public schools' student–teacher ratios compared to less-developed provinces. However, the private schools' student–teacher ratios in more developed provinces, especially in senior secondary school, are lower than those in less-developed provinces. This might indicate that public schools are inadequate in more-developed provinces, as those provinces tend to have a higher population density. In the absence of public facilities, more-developed provinces, therefore, rely on the existence of private schools to cover their needs for quality education. This situation can imply higher disparity in educational attainment during the pandemic, when households that can afford private education are more prepared in facing the new-normal class environment. This result also supports our initial hypothesis that richer and more-developed regions have better learning outcomes, and distance learning will exacerbate this gap.

Our series of estimations on search intensity provide us with interesting results. Indeed, the high surge in online classroom related search intensity is caused by the school closures due to the COVID-19 pandemic from 16 March 2020, especially during the early weeks after the closures. However, the school closures do not seem to impact the pattern of the self-learning related search intensity. We also find that different levels of per capita expenditure between provinces only create small gaps in the search intensities for both online classroom and self-learning related keywords since all provinces receive a high surge in search intensity, particularly for online classroom related keywords. However, inequality indicators within provinces, proxied by the provincial Gini coefficient and the share of the rural population, become major factors in creating learning engagement gaps, where a higher Gini coefficient or higher share of rural population reduces online classroom related search intensity. In addition, a higher share of the rural population also increases the self-learning related search intensity as students in rural areas are forced to offset the inadequacy of formal school learning materials by conducting more self-learning activities. This fact is reinforced by having a higher school-quality index that actually lowers the self-learning related search intensity. These results imply that socio-economic inequality, particularly between urban and rural areas, contributes to wider gaps in online learning engagement and, therefore, a widening of the gaps between learning effectiveness and quality amongst students.

Interestingly, technology adoption measures do not seem to majorly affect online classroom related search intensity. Instead, higher technology adoption contributes to lower self-learning related search intensity. We argue that this is caused by increasing academic distraction as students with better internet access utilise it for online recreational activities rather than learning, a pattern that seems to be growing in the pandemic.

Our study has multiple limitations. First, we are unable to point out the exact numbers of the effective student-to-teacher ratio or classroom-to-teacher ratio, and our data limits us in precisely identifying schools' class capacity. Thus, our analysis for the limited classroom scenario is limited as we can only identify which regions are lacking in those categories. Second, there is no more granular level of search intensity as Google Trends does not capture data at the municipality level. Third, since national exams were removed from 2020 onwards, we are unable to clearly identify the potential learning loss post-pandemic. Lastly, our study only captures online learning engagement, not online learning effectiveness or the quality that is related to the materials provided in the online classrooms. However, several studies have already pointed out that online classrooms are less effective than offline classrooms, especially in developing countries.

5.2. Policy implications

Based on our study, our proposed policy recommendations for the Government of Indonesia are as follows:

1. Increasing the students-per-classroom capacity in densely populated areas and the quality of the learning materials in less-developed, particularly rural, areas. Going with the limited classroom scenario can be detrimental in highly populated areas since schools' capacity is inadequate to manage less classroom capacity. On the other hand, online classroom effectiveness is severely limited in less developed regions as schools cannot adequately provide good online learning materials.
2. Increasing the scope of reliable internet access in all regions by developing digital infrastructure.
3. Encouraging students to conduct more online self-learning activities and parents to assist their children in distance learning. Our study shows that self-learning activities are lower in provinces with high technology adoption due to distraction. Therefore, schools must actively encourage students to study by themselves and parents to assist them.

Ultimately, as stated by Kimura (2020), mandatory social distancing is changing how the economy and society work, and digital connectivity has become a crucial component in the concurring pandemic. Our study can help to provide perspective on the needs of digital connectivity and extrapolate the results of our study for other ASEAN Member States that have a huge digital divide across regions and differing socio-economic status. In addition, as more ASEAN Member States have planned to reopen schools, our case study on Indonesia can be beneficial for them to anticipate issues that could potentially emerge in the implementation.

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Appendix 1. Constructing the school quality index

We construct the school quality index using multiple factor analysis to reduce the dimensions of several databases into one dimension. In this case, multiple factor analysis is the most appropriate method to use since there are several ordered non-binary categorical variables to consider. The list of variables, which we also scaled to 0 and 1, are shown in Table A1.1.

Table A1.1. List of Variables for School Quality

Soap availability
Toilet type
Restrooms per student
Laboratories per student
Libraries per student
Classes per student
Sink availability
Water adequacy
Water availability
Processed water availability
Water source
Drinking water availability
School staff per student
Teachers per student
Electricity availability
Electricity watts
Internet availability

We decided to take two factors as our base to create the index as they capture 94% of the data variance. Fortunately, the variables are divided neatly into these two factors as shown by Figure A1.1, making them easier to classify. Therefore, we classify the variables into these two factors according to their closeness or eigenvalue, and as a result we divided the variables as follows.

Figure A1.1. Loading Plot

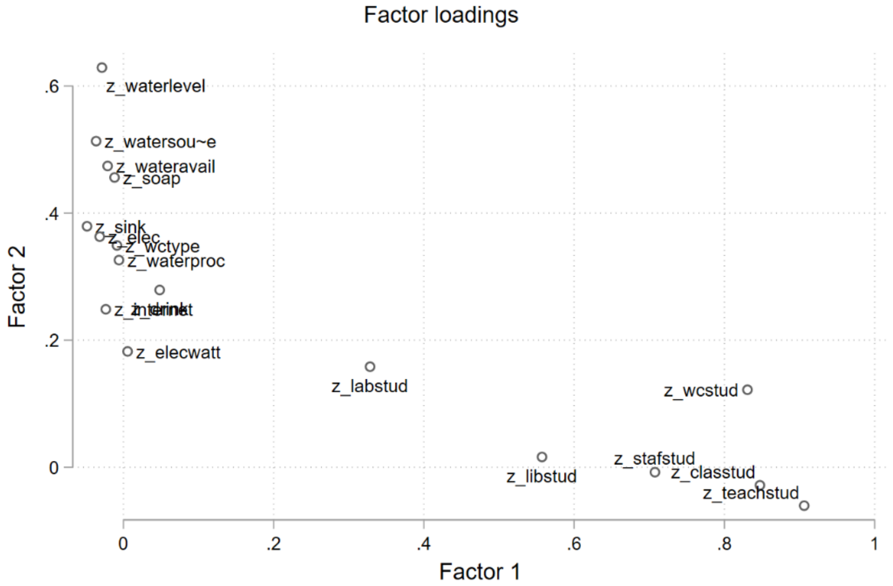
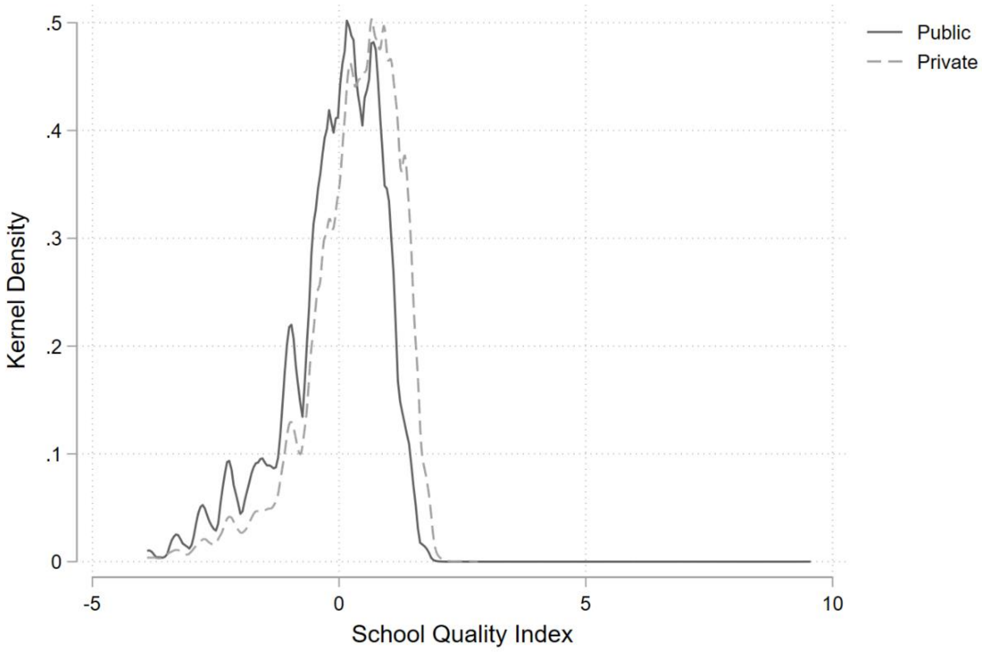


Table A1.2. Eigenvalues for All Variables in Two Factor Loadings

Variable	Factor1	Factor2
Soap availability		0.4561
Toilet type		0.3491
Restrooms per student	0.8307	
Laboratories per student	0.3283	
Libraries per student	0.5572	
Classes per student	0.8473	
Sink availability		0.3793
Water adequacy		0.629
Water availability		0.4742
Processed water availability		0.3261
Water source		0.5133
Drinking water availability		0.279
School staff per student	0.7075	
Teachers per student	0.9062	
Electricity availability		0.363
Electricity watts		0.1823
Internet availability		0.2487

Then, we classify the index by summing all of the variables' values multiplied by their respective eigenvalues. Finally, we normalised the summed values by the mean and standard deviation to obtain the index. Figure A1.2 shows the aggregate distribution of the school infrastructure quality index.

Figure A1.2. Kernel Density of the School Quality Index



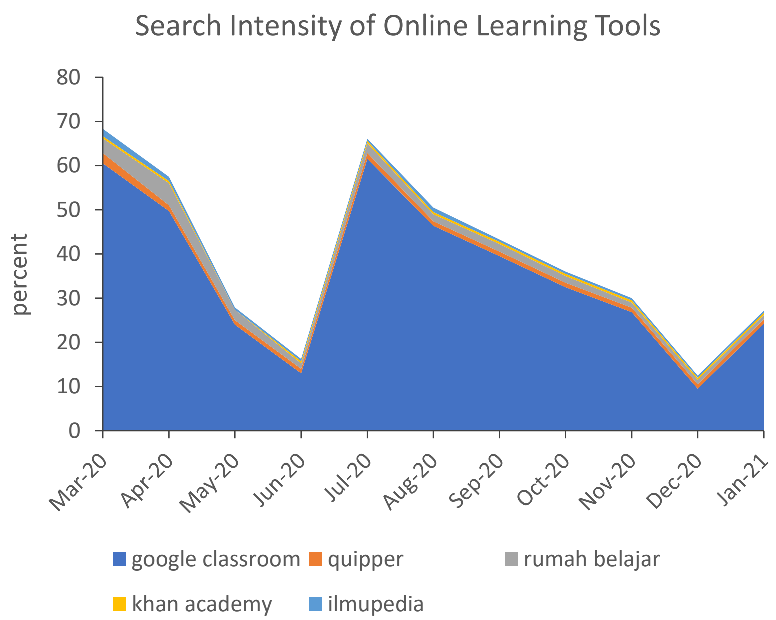
Appendix 2. Number of Schools by Type and Region

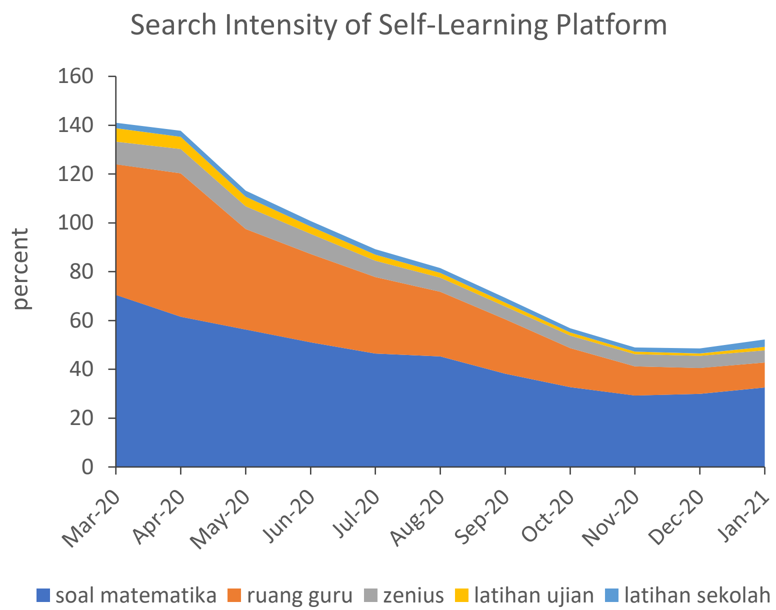
Province	Primary school			Special needs school			Senior high school			Vocational school			Junior high school			Grand Total
	Public	Private	Total	Public	Private	Total	Public	Private	Total	Public	Private	Total	Public	Private	Total	
Aceh	3338	153	**3491**	30	47	**77**	396	130	**526**	150	66	**216**	894	276	**1170**	**5480**
Bali	2315	133	**2448**	11	2	**13**	80	81	**161**	51	121	**172**	271	151	**422**	**3216**
Banten	3955	679	**4634**	7	92	**99**	152	418	**570**	80	650	**730**	563	936	**1499**	**7532**
Bengkulu	1305	83	**1388**	13	4	**17**	110	33	**143**	64	40	**104**	379	48	**427**	**2079**
D.I. Yogyakarta	1431	413	**1844**	9	70	**79**	69	94	**163**	50	170	**220**	214	229	**443**	**2749**
D.K.I. Jakarta	1464	913	**2377**	13	78	**91**	117	375	**492**	73	513	**586**	293	777	**1070**	**4616**
Gorontalo	920	24	**944**	8		**8**	58	8	**66**	40	17	**57**	315	23	**338**	**1413**
Jambi	2314	132	**2446**	13	5	**18**	161	74	**235**	104	73	**177**	555	123	**678**	**3554**
Jawa Barat	17571	2045	**19616**	39	343	**382**	508	1153	**1661**	287	2651	**2938**	1939	3479	**5418**	**30015**
Jawa Tengah	17774	1187	**18961**	39	149	**188**	360	508	**868**	237	1351	**1588**	1770	1584	**3354**	**24959**
Jawa Timur	17366	1874	**19240**	71	370	**441**	423	1109	**1532**	297	1806	**2103**	1725	3055	**4780**	**28096**
Kalimantan Barat	4129	275	**4404**	13	9	**22**	264	177	**441**	107	116	**223**	1005	317	**1322**	**6412**
Kalimantan Selatan	2779	154	**2933**	20	7	**27**	136	59	**195**	61	64	**125**	521	92	**613**	**3893**
Kalimantan Tengah	2433	210	**2643**	19	5	**24**	181	59	**240**	94	43	**137**	702	135	**837**	**3881**
Kalimantan Timur	1654	238	**1892**	10	25	**35**	140	87	**227**	87	135	**222**	440	217	**657**	**3033**
Kalimantan Utara	435	43	**478**	5		**5**	42	19	**61**	18	11	**29**	148	32	**180**	**753**
Bangka Belitung	757	59	**816**	7	2	**9**	44	26	**70**	36	22	**58**	161	54	**215**	**1168**
Riau	684	277	**961**	8	9	**17**	91	57	**148**	35	78	**113**	233	148	**381**	**1620**
Lampung	4355	356	**4711**	11	16	**27**	239	264	**503**	109	372	**481**	701	662	**1363**	**7085**
Maluku	1259	532	**1791**	9	5	**14**	209	73	**282**	81	32	**113**	514	144	**658**	**2858**
Maluku Utara	1107	205	**1312**	15	4	**19**	137	71	**208**	63	76	**139**	355	137	**492**	**2170**

Nusa Tenggara Barat	3010	211	**3221**	16	29	**45**	158	174	**332**	97	228	**325**	607	344	**951**	**4874**
Nusa Tenggara Timur	3337	1808	**5145**	29	7	**36**	348	204	**552**	145	147	**292**	1318	421	**1739**	**7764**
Papua	1621	953	**2574**	6	3	**9**	137	93	**230**	78	58	**136**	497	203	**700**	**3649**
Papua Barat	675	396	**1071**	4	1	**5**	77	45	**122**	32	22	**54**	222	88	**310**	**1562**
Riau	3201	507	**3708**	17	30	**47**	302	147	**449**	125	174	**299**	847	347	**1194**	**5697**
Sulawesi Barat	1300	29	**1329**	13	12	**25**	75	13	**88**	59	76	**135**	313	60	**373**	**1950**
Sulawesi Selatan	6106	308	**6414**	23	63	**86**	336	244	**580**	168	273	**441**	1262	418	**1680**	**9201**
Sulawesi Tengah	2668	237	**2905**	18	11	**29**	175	48	**223**	105	79	**184**	725	118	**843**	**4184**
Sulawesi Tenggara	2249	71	**2320**	17	57	**74**	237	56	**293**	101	60	**161**	688	77	**765**	**3613**
Sulawesi Utara	1377	858	**2235**	6	24	**30**	120	104	**224**	90	97	**187**	473	251	**724**	**3400**
Sumatera Barat	3993	240	**4233**	29	123	**152**	236	96	**332**	114	101	**215**	676	150	**826**	**5758**
Sumatera Selatan	4288	390	**4678**	14	20	**34**	326	268	**594**	114	192	**306**	896	466	**1362**	**6974**
Sumatera Utara	8299	1470	**9769**	29	29	**58**	427	661	**1088**	267	733	**1000**	1323	1300	**2623**	**14538**
Grand Total	**131469**	**17463**	**148932**	**591**	**1651**	**2242**	**6871**	**7028**	**13899**	**3619**	**10647**	**14266**	**23545**	**16862**	**40407**	**219746**

Source: Data are from https://dapo.kemdikbud.go.id/; authors' calculations

Appendix 3. Comparison of Search Intensity Between Keywords



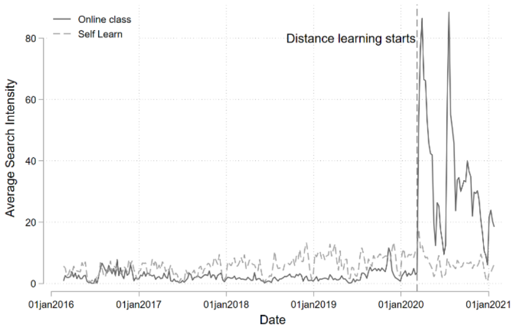


Note: The search intensity per keyword is presented in the monthly average, as relative to the total search intensity of all keywords.

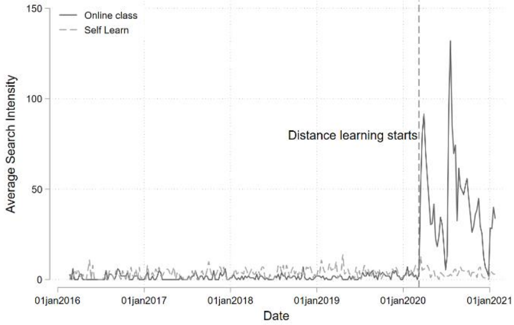
Source: Google Trends.

Appendix 4. Search Intensity by Region

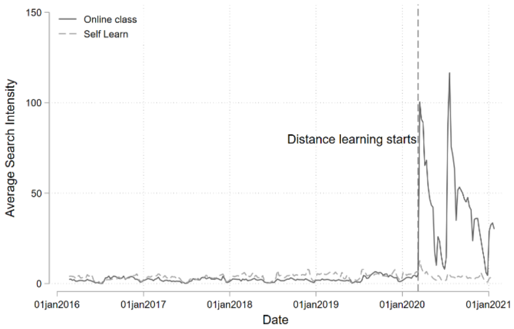
Sumatera & Aceh



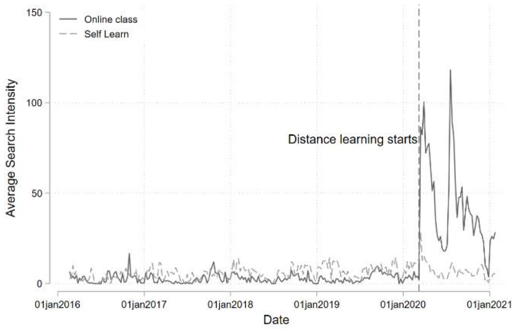
Riau Islands



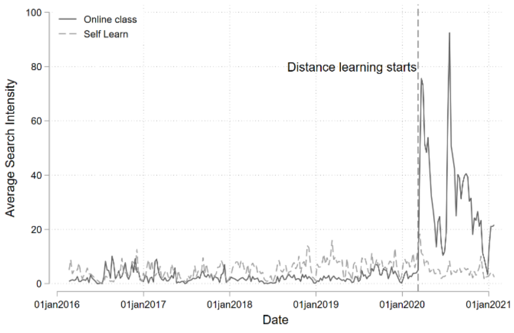
Java



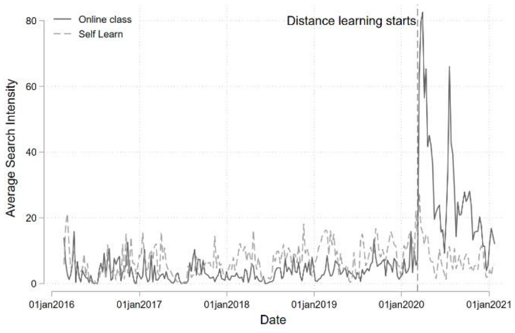
Bali & NT



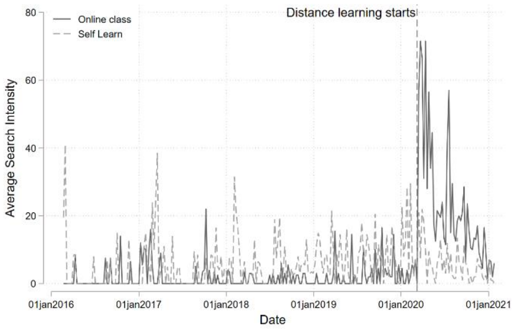
Kalimantan



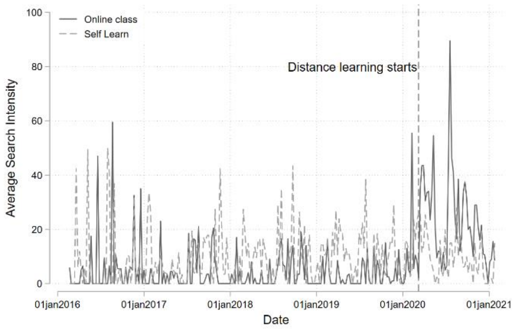
Sulawesi



Maluku



Papua



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