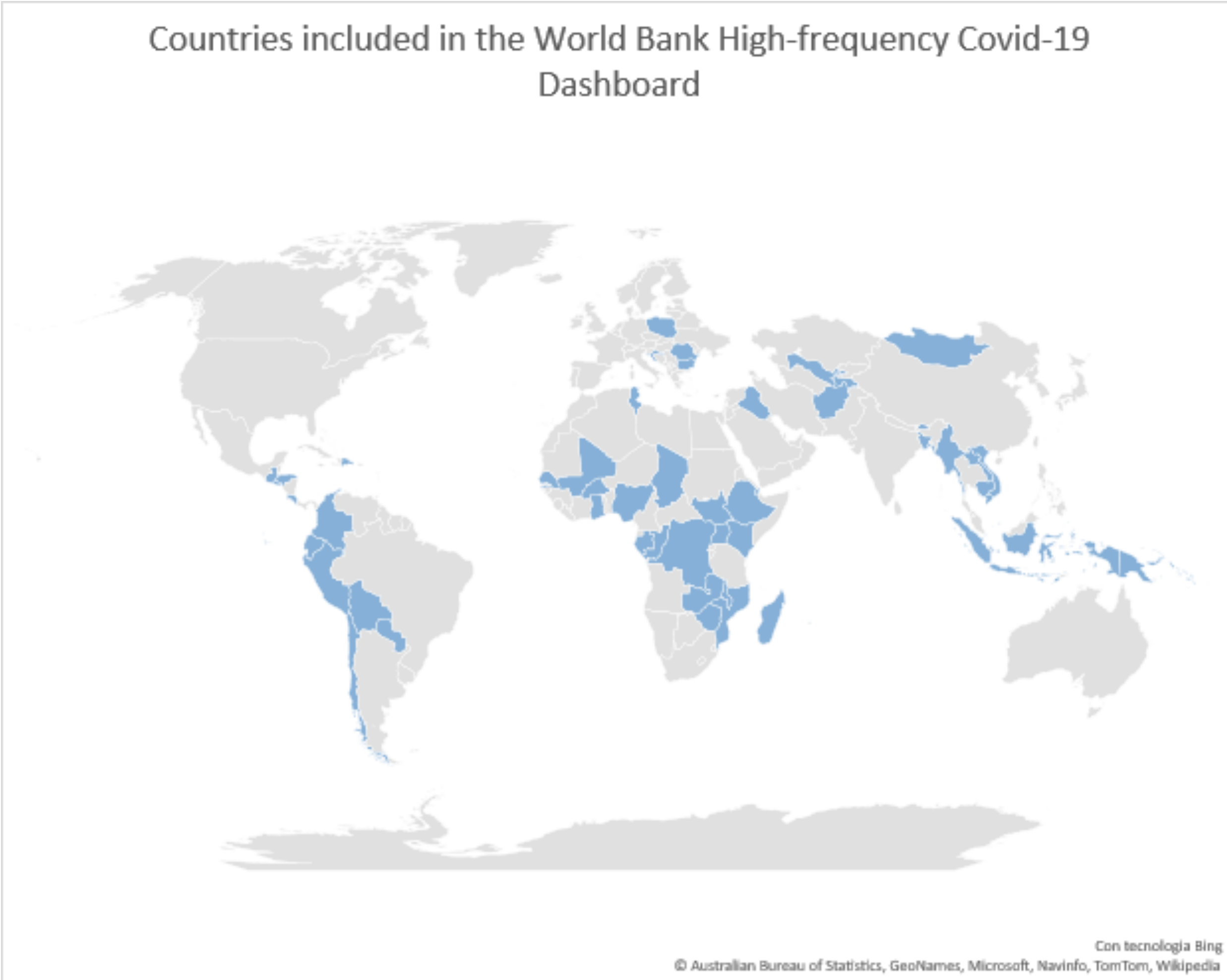
Annex

Data Sources

In this paper we rely on two primary sources of data. The first is nationally representative household survey data collected by the World Bank and systematized in the COVID-19 High Frequency Monitoring Dashboard. As of 22nd April 2021, information comes from 54 countries across different geographic regions, namely Sub-Saharan Africa (20 countries), Latin America & The Caribbean (12 countries), East Asia & Pacific (9 countries), Europe and Central Asia (6 countries), Middle East and North Africa (4 countries) and South Asia (3 countries). **Figure 1** shows the geographic distribution of the countries included across the globe. In **Table 2**, the breakdown of these countries by food system typology is presented. The data we use in this study come from low- and middle-income countries and include three of the four food system typologies: rural and traditional (23 countries), informal and expanding (14 countries), emerging and diversifying (10 countries), and modernizing and formalizing (7 countries)

Figure 1. Geographic distribution of countries included in the World Bank High-Frequency COVID-19 Dashboard (April 22nd, 2021)



Source: self-elaborated using data from World Bank COVID-19 High-Frequency Monitoring Dashboard

Table 2. List of countries included in the World Bank COVID-19 High Frequency Monitoring Dashboard (April 22nd, 2021)

Food-System Typology	Country Name	Region
Rural and Traditional	Papua New Guinea	East Asia & Pacific
	Lao PDR	East Asia & Pacific
	Cambodia	East Asia & Pacific

	Tajikistan	Europe & Central Asia
	Djibouti	Middle East & North Africa
	Palestinian Territories	Middle East & North Africa
	Burkina Faso	Sub-Saharan Africa
	Central African Republic (Bangui/Bimbo)	Sub-Saharan Africa
	Ethiopia	Sub-Saharan Africa
	Kenya	Sub-Saharan Africa
	Madagascar	Sub-Saharan Africa
	Mali	Sub-Saharan Africa
	Chad	Sub-Saharan Africa
	South Sudan	Sub-Saharan Africa
	Democratic Republic of the Congo	Sub-Saharan Africa
	Uganda	Sub-Saharan Africa
	Mozambique	Sub-Saharan Africa
	Malawi	Sub-Saharan Africa
	Zambia	Sub-Saharan Africa
	Zimbabwe	Sub-Saharan Africa
	Afghanistan	South Asia
	Bangladesh	South Asia
	Bhutan	South Asia
Informal and Expanding	Solomon Islands	East Asia & Pacific
	Indonesia	East Asia & Pacific
	Myanmar	East Asia & Pacific
	Philippines	East Asia & Pacific
	Vietnam	East Asia & Pacific
	Uzbekistan	Europe & Central Asia
	Bolivia	Latin America & Caribbean
	Guatemala	Latin America & Caribbean
	Honduras	Latin America & Caribbean
	Iraq	Middle East & North Africa
	Ghana	Sub-Saharan Africa
	Nigeria	Sub-Saharan Africa
	Senegal	Sub-Saharan Africa
	Republic of the Congo	Sub-Saharan Africa
Emerging and Diversifying	Mongolia	East Asia & Pacific
	Romania	Europe & Central Asia

	Ecuador	Latin America & Caribbean
	Peru	Latin America & Caribbean
	Paraguay	Latin America & Caribbean
	El Salvador	Latin America & Caribbean
	St. Lucia	Latin America & Caribbean
	Tunisia	Middle East & North Africa
	Gabon	Sub-Saharan Africa
	Mauritius	Sub-Saharan Africa
Modernizing and Formalizing	Bulgaria	Europe & Central Asia
	Croatia	Europe & Central Asia
	Poland	Europe & Central Asia
	Chile	Latin America & Caribbean
	Colombia	Latin America & Caribbean
	Costa Rica	Latin America & Caribbean
	Dominican Republic	Latin America & Caribbean

Source: World Bank. "COVID-19 High frequency Monitoring Dashboard". The World Bank Group. Washington, DC. 2021. COVID-19 High-Frequency Monitoring Dashboard (worldbank.org)

Data comes from different national questionnaires collected through high-frequency phone surveys, which have been harmonized by the World Bank into 95 indicators covering 13 different topics (see **Annex 1).** This harmonization process, which entails mainly renaming and recoding categories to be consistent with a common template, allows comparability across countries. It is worth noting that some questions might be missing from some national survey, therefore the number of countries might vary depending on the indicator. Also, surveys have been repeated in several waves to allow monitoring across time, though such waves have not been executed simultaneously in all the 54 countries, meaning that the same wave (1st, 2nd, 3rd, etc…) might have been collected in different months for different countries. Finally, the number of times such surveys have been repeated it is not homogenous across countries.

This paper focuses on 19 indicators across 3 topics, namely: food security, coping and income. The full list of indicators is found **Table 3**. Different methodologies have been used to design nationally representative samples. Where countries had recently conducted representative household survey, contact information of respondents was used to create a representative subsample. When this approach was not possible, contact information was retrieved from other sources, such as government registries, telecommunications companies, or marketing firms. In Latin America and the Caribbean (LAC), samples are generated through a Random Digital Dialling (RDD) process, ensuring coverage of all landline and cell phone numbers active at the time of the survey.

While phone surveys have proved to be a useful data collection tools during the pandemic, they do have some limitations that are important to mention. First, individuals without access to phone or with limited network coverage, which normally belong to the poorest and most remote social categories, are under-represented in the sample. Second, they are affected by high levels of non-response and attrition. Third, a trade-off had to be made between the breadth and depth of the questions asked, and the length of the calls. Fourth, all questions are asked to a single respondent per household, therefore individual-level answers might be biased by respondent selection. Finally, in countries where the High-Frequency Phone Surveys panel is a sample from existing pre-covid national surveys, the designated respondent is the household head, therefore data on employment might differ from those measured by conventional Labour Force Surveys due to characteristics related to being the head of household, such as gender and age. To correct for such biases, household level weights have been applied to the data in the Dashboard. Since countries in the LAC region adopted the RDD sampling process, weights differ slightly. In such countries two sets of weights have been generated to correct for selection bias due to the probability of phone-ownership and nonresponse rate, one at household level and one at individual level. Moreover, weights have been adjusted for attrition in subsequent survey waves[1].

Table 3. List of indicators from World Bank High Frequency COVID-19 Monitoring Dashboard included in the analysis.

Food Security[2]:

- **Able to access any staple food in the past 7 days - all staple food items (% of HHs)**: household-level dummy variable indicating whether household was able to access any staple food in the past 7 days. The indicator takes the value of 1 if the answer is "yes".
- **In the last 30 days, went without eating for a whole day due to lack of money (% of HHs)**: dummy variable indicating whether any adult in the household went without eating for a whole day due to lack of sufficient income in the last 30 days. The indicator takes the value of 1 if answer is "yes". This indicator is part of the standard Food Insecurity Experience Scale (FIES).
- **In the last 30 days, were hungry but did not eat due to lack of money (% of HHs)**: dummy variable indicating whether any adult in the household was hungry but could not eat due to lack of sufficient income in the last 30 days. The indicator takes the value of 1 if answer is "yes". This indicator is part of the standard Food Insecurity Experience Scale (FIES).
- **In the last 30 days, ate only a few kinds of foods due to lack of money (% of HHs)**: dummy variable indicating whether any adult in the household ate only few kinds of food due to lack of sufficient income in the last 30 days. The indicator takes the value of 1 if answer is "yes". This indicator is part of the standard Food Insecurity Experience Scale (FIES).
- **In the last 30 days, was anyone unable to eat healthy/nutritious or preferred food due to lack of resources (% of HHs)**: dummy variable indicating whether any adult in the household was unable to eat healthy/nutritious food due to lack of sufficient income in the last 30 days. The indicator takes the value of 1 if answer is "yes". This indicator is part of the standard Food Insecurity Experience Scale (FIES).

Income[3]:

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[1] For more information on weights refer to the COVID-19 High-Frequency Monitoring Dashboard Technical Note (covid19dashboardtechnicalnote.pdf (development-data-hub-s3-public.s3.amazonaws.com))

[2] For analytical purposes, we used only food security data collected in June 2020.

[3] For analytical purposes, we used only data collected on the first survey wave to assess the impact on income since the start of the pandemic

- **Experienced decrease in total income since the beginning of the pandemic (% HHs)**: household-level dummy variable indicating whether household experienced a decrease in income compared to pre-pandemic levels. The indicator takes the value of 1 if the answer is "yes".
- **Experienced decrease in remittances since the beginning of the pandemic (% of remittance receiving HHs)**: household-level dummy variable indicating whether household experienced a decrease in remittances since the start of the pandemic. The indicator takes the value of 1 ("yes") if the household was receiving remittances before the pandemic, and experienced a decrease compared to pre-pandemic levels.
- **Experienced decrease in wage income since the beginning of the pandemic (% HHs with wage income as a source of livelihood in the past 12 months)**: household-level dummy variable indicating whether household experienced a decrease in wage income since the start of the pandemic. The indicator takes the value of 1 ("yes") if wage was a source of income for the household in the previous 12 months, and it experienced a decrease compared to pre-pandemic levels.
- **Experienced decrease in income from non-farm family business since the beginning of the pandemic (% HHs with non-farm business income as a source of livelihood in the last 12 months)**: household-level dummy variable indicating whether the household experienced a decrease in non-farm business income since the start of the pandemic. Indicator takes the value of 1 ("yes) if non-farm business was an income source in the previous 12 months, and household experienced a decrease compared to pre-pandemic levels.
- **Experienced decrease in farm income since the beginning of the pandemic (% HHs with farm income as a source of livelihood in the last 12 months)**: household-level dummy variable indicating whether the household experienced a decrease in farm income since the start of the pandemic. Indicator takes the value of 1 ("yes) farm was a source of income in the previous 12 months, and household experienced a decrease compared to pre-pandemic levels.
- **Currently employed/working (% of respondents above 18 years old)**: individual-level dummy variable indicating whether individual is currently employed. Indicator takes the value of 1 if the answer is "yes".
- **Engaged in farming activities (% of HHs)**: individual-level dummy variable indicating whether individual is engaged in farming activities. Indicator takes the value of 1 if the answer is "yes".
- **Engaged in non-farm enterprises (% of HHs)**: individual-level dummy variable indicating whether individual is engaged in non-farming activities. Indicator takes the value of 1 if the answer is "yes".
- **Unable to perform normal farming activities (crop, livestock, fishing) (% of HHs)**: individual-level dummy variable indicating whether individual is engaged in non-farming activities. Indicator takes the value of 1 if the answer is "yes".
- **Stopped working since COVID-19 outbreak (% of respondents who worked before pandemic and above 18 years old)**: individual-level dummy variable indicating whether individual is engaged in non-farming activities. Indicator takes the value of 1 ("yes") if respondent was working before the pandemic, and he is not working anymore since the covid outbreak.
- **Unable to work as usual last week (% of respondents in wage employment and above 18 years old):** individual-level dummy variable indicating whether individual was unable to work as usual the previous week. Indicator takes the value of 1 ("yes") if respondent was working in wage employment the week before, he is not working anymore.

Coping:

- **Sold assets to pay for basic living expenses during the pandemic (% of HHs)**: household-level dummy variable indicating whether household had to sell assets to cover basic expenses during the pandemic. Indicator takes the value of 1 if the answer is "yes".
- **Used emergency savings to cover basic living expenses during the pandemic (% of HHs)**: household-level dummy variable indicating whether household used emergency savings to cover basic expenses during the pandemic. Indicator takes the value of 1 if the answer is "yes".
- **Reduced consumption of goods (essential or non-essential) during the pandemic (% of HHs)**: household-level dummy variable indicating whether household reduced consumption of essential and non-essential goods during the pandemic. Indicator takes the value of 1 if the answer is "yes".

Source: COVID-19 High-Frequency Monitoring Dashboard Technical Note (covid19dashboardtechnicalnote.pdf (development-data-hub-s3-public.s3.amazonaws.com))

The second data source comes from a systematic mapping of available empirical literature in English, French, and Spanish on the impacts of COVID-19 in rural spaces. This exercise is a combination of machine learning, web-based search queries and manual categorization. It involves three stages: first a two-step procedure for harvesting and indexing relevant papers, followed by a further filter of machine and manual learning classification.

The first step of the first stage of the systematic mapping was a query-based harvesting or scraping of documents from a number of selected web-based sources. Of these sources, some are aggregators, chosen because of their broad coverage, like Google or CrossRef, while others are more specialized repositories, which were chosen on the basis of having strong level of reliability in terms of coverage and level of "knowledge validation" (e.g. Technical reports from reliable institutions such as World Bank and other UN Organizations) (**Annex 2** for the complete list). The effectiveness of the query and the recall/precision of the search depended very much on the search capabilities of the search interface of the source and on its level of openness. Some sources utilize Application Programming Interfaces (APIs) that support several filters and advanced queries with operators, while others only support a simple free-text search; some provide full direct access to the PDFs, some provide IP or authentication-based access, and others only display PDFs in web viewers. Due to these differences, the query and filters used on each source were different (see **Annex 2**), and the percentage of relevant results that could be downloaded from each source varies, going from almost 100% in open institutional repositories to much lower rates in big aggregators like Google. In general, since this was only the first step of the selection, the approach was to use very broad queries (often just "covid") whenever complex queries were not allowed. All the documents identified through the queries were then automatically downloaded and passed to the second step.

The *second step* was a topic-based indexing of articles to automatically filter harvested and web-scraped texts and data and only retain those relevant for our analysis, namely documents that covered at the same time COVID-19 and rural poverty (articulated around the concepts of food security, coping strategies, production and income) and contained data analysis – specifically micro data - highlighting change (improvement, worsening, increase, decrease…). To do this, key concepts were identified around 7 topics, of which 5 were mandatory (keywords from each of these topics had to be present): COVID-19, poverty, agri-food/rural, data analysis and "change"; and 2 optional (keywords from these topics were not mandatory but added to the relevance): value chains and micro-data. These key concepts were expanded into a set of keywords with synonyms and translations in Spanish and French through an algorithm based on multilingual lexical resources (see **Table 4** for the complete list of concepts and keywords). A text-mining procedure analyzed all downloaded documents against these keywords and assigned scores against each topic and a final combined relevance for our research. A total of 1901 documents above a certain threshold of relevance were retained for the third step (see **Table 5**)[4].

Table 4. List of Mandatory Topic and Keywords

POVERTY	COVID19	AGRIFOOD	CHANGE	DATA-ANALYSIS
poverty	COVID-19	agriculture	leap	analysis
income	pandemic	crops	affect	comparison group
household welfare / wellbeing	quarantine	farmers	hit	estimation
credit		alimentation	impact	proportion/percent/rate
assets (incl. investment and capital)		fisheries	change	data
remittances		fishermen	difference	sample
labor supply		food	transformation	survey
employment		forestry	comparison	empirical approach
international migration		hunger	high	method
type of labor: job/occupation		livestock	low	methodology
health services		herdsman/pastoralism	measure	model
insecurity		rural	quantity	
hunger / malnutrition			scarcity	
food security			better	
consumption			effect	
education			improvement	
resilience			worse	
			worsening	
			decrease	
			increase	
			trend	

The second stage involved a machine learning approach using a Logistic TF-IDF (Term Frequency-Inverse Document Frequency) algorithm. In this stage the machine was first trained to classify the documents as "relevant" or "not-relevant" based on a set of papers provided by the researchers containing examples of both relevant and non-relevant documents. The machine attributes a score to each paper measuring the likelihood of a paper of containing relevant information, and a cut-off point is established to separate

[4] For the purpose of writing this paper, the last web-based search was conducted on April 16th, 2021.

those relevant (above the threshold) from those that are not relevant (below the threshold).[5] After the training phase, the model is applied to the whole dataset, so that all the 1901 papers downloaded in stage 1 were classified as "relevant" or "non relevant". Then a manual check was conducted to confirm the validity of the model and retrain it if necessary[6]. The model is then re-applied to the whole set of downloaded documents to give a more precise classification based on the retraining of the model. These last two steps of the machine learning approach are conceived as iterative process whereby new samples of documents are periodically checked after the machine categorization and can be repeated until the accuracy of the classification is satisfactory to the researchers. At the end of this iterative procedure a total of 157 documents were classified as "relevant" by the machine (see **Table 5**).

For the third stage, once relevant papers were identified, quantitative data related to impacts of the pandemic on income, including farm production, coping strategies, and food security in rural areas was extracted from 39 papers and included in our systematic review database (see **Table 5**)[7]. For the purpose of writing this paper, extraction followed a precise set of criteria based on discernible characteristics reported in **Table 6** with the aim of creating a database of quantitative impacts of COVID-19 in rural areas. Although all the 157 papers identified by the machine are relevant for understanding the socio-economic impacts of COVID-19 in rural areas, not all of these included the required information at household level for the indicators of interest. Also, 13 World Bank High-Frequency Phone Survey reports were downloaded through the web-search and rightfully classified as relevant by the machine, though we decided not to extract information from these reports because the data used are already included in our analysis. This explains why the number of papers from which information was extracted (i.e. 39) differs from the number of papers classified as relevant (i.e. 157).

Of course, within each of these broad thematic categories there is considerable variation between papers in terms of the specific indicators used. To enable comparability between these papers and the nationally representative data collected through the World Bank HFPS initiative, we cluster the unique indicators from the literature into broader categories that are consistent with the harmonized indicators collected by the World Bank. The thematic clusters, specific indicators, and number of papers containing relevant information is summarized in **Annex 3**.

Table 5. Stages

	N. of papers included
1) *Web-based query search*	1901
2) *Machine Learning relevance stage*	157
3) *Extraction process*	39

[5] The tf–idf is the product of two statistics, *term frequency* and *inverse document frequency* and is a formula that aims to define the importance of a keyword or phrase within a document. *Term frequency* refers to the number of times that a certain term occurs in document in a document while *inverse document frequency* is a measure of how much information the word provides, i.e., if it's common or rare across all documents.

[6] This was done by two independent researchers to reduce bias. Documents were sorted according to their relevance score, and the first 30 documents classified as "relevant" and "non relevant" were checked. Indeed, by manually confirming or editing the classification conducted by the machine, the model automatically updates its training parameters (in simple terms it learns which words are most likely identify relevant documents)

[7] Systematic Review Database contains information extracted from a total of 39 relevant papers. A total of 13 World Bank HFPS reports were downloaded and categorized as relevant by the machine, though information was not included in the Systematic Review Database since it was already systematized in the World Bank COVID-19 High-Frequency Monitoring Dashboard. On the other hand, data from 1 document using World Bank HFPS data was extracted and included in the Systematic Review Database, since more complex statistical analysis was conducted.

Table 6. Criteria of relevance

Criteria	*Paper requisite*
Data	Includes quantitative data
	Includes outcome indicators
	Containing estimates or measures of impacts
	Rigorous sampling methodology
Level of analysis	Household level indicators
Area of interest	Analyzing impacts on Low and middle income countries
	Rural areas
	Agricultural sector

This data extraction and clustering process serves three main purposes in this paper. First, it allows us to validate the impact measurements coming from the World Bank COVID-19 High-Frequency Monitoring Dashboard against other quantitative data sources. This is important because, as discussed in Brubaker et al., (2021), there are structural difference between phone survey respondents included the World Bank datasets relative to the wider population, which are not completely eliminated through individual weighting. In particular, in Ethiopia, Malawi, Nigeria, and Uganda they found that respondents are significantly more likely to be household heads or their spouses, and they tend to be older, more educated, and more likely to own a household enterprise than the general population (ibid). Second, the papers identified through the systematic mapping exercise often provide contextual information on the impact pathways that is not available in aggregate national statistics. We, therefore, make use on the findings from the literature to provide contextual insights explaining how and why patterns and variations in outcomes occur. Thirdly, we used the systematic review to fill gaps on topics of interest to this paper when World Bank data was not available, as in the case of specific variables related to agricultural production (see Table 8).