A Brief Literature Review of Structuring District Heating Data based on Measured Values

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ABSTRACT. This study reviews existing literature regarding district heating (DH) data and its clustering. In district heating, heat is produced at a central plant and supplied via a pipeline network to consumers (for example: homes, businesses, and industrial facilities). Different approaches were used—some based on consumption data and others based on heat load/demand data. Common methodology was researched and checked. New methods were double checked if reused in related work or developed single purpose only. Most databases are highly susceptible to being inconsistent, incomplete (lacking attribute values), and/or noisy (containing errors or outlier values). The major obstacle to obtain knowledge is poor data. It is necessary, therefore, to ensure that the knowledge discovered from the databases is, in fact, reliable. The PRISMA flow chart was applied to screen over 60 articles and to perform the literature review. As a result, 12 papers were identified dealing with the structuring of district heating data—almost all use either K-means methodology directly or another methodology based on K-means. Additionally, this study identified a research gap regarding eastern Europe in the data used and descriptions of applied methods.

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INTRODUCTION

Understanding energy user consumption patterns benefits both utility companies and consumers, as it can support improving energy management and usage strategies. The heat usage of customers is crucial for effective district heating (DH) operations and management. Unfortunately, existing knowledge about customers and their heat load behaviors is quite scarce (Calikus et al. 2019). Most previous studies are limited to small-scale analyses that are not representative enough to understand the behavior of the overall network. Contrary to electricity smart-meter data analysis, little research regarding district heat smart-meter data has been published. The deployment of smart meters offers a unique opportunity for researchers and district heating utilities to analyze large-scale data and discover both typical and atypical patterns in the network. The aim is to focus on local needs and take a scientific, methodological approach to local problem solving.

As defined by Wikipedia (2022a): “District heating (also known as heat networks or teleheating) is a system for distributing heat generated in a centralized location through a system of insulated pipes for residential and commercial heating requirements such as space heating and water heating.” A power plant, solar thermal or geothermal installation, or a large heat pump is used to heat a fluid (mainly water with additives) which is then fed into a network of insulated (and usually buried) pipes. These pipes lead straight into the buildings connected to the system. The water then flows through a handover station and into the building’s heat distribution system, which provides for a supply of heating energy and hot water. Once the water has cooled down, it flows back to the original heat source and the cycle begins anew. Buildings that are supplied with district heating do not need their own heating systems and chimneys. District heating systems are supply systems consisting of many components: district heating plants, plants for maintaining pressure and volume, facilities for water treatment and district heating transport, distribution networks, and customer transfer stations. Because such a system must always be in equilibrium between district heating output and generation, an additional heating center is responsible for the efficient control of the system.

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Sustainable development (SD) is a multi-aspect and complicated concept, and measuring it requires data from a wide range of indicators (Mirghaderi and Mohit-Ghiri 2019). To help cities plan for sustainability, companies and organizations have created a wide variety of networks and benchmark systems that collect, measure, and rank sustainability. This aids cities to develop and apply practical strategies, tools, and methodologies or provide a venue to share best practices and lessons learned around sustainability. Analyzing the data of smart meters enables energy savings and integration of renewable energy resources and is a component on its own (Radtke and Kaempf 2021). Finally, local conditions—and the requirements and support from the European Union—play a role that should not be underestimated.

Clustering district heating data is mainly based on 2 different dimensions: demand and/or consumption. Smart-meter data are mainly available for electricity, and thus, consumption-based data are available and measured (Völker et al. 2021). For district heating, few installations use consumption-based data; however, demand for mainly heat substations or large buildings (consisting of several flats) is available and used. This systematic literature review will shed light on both the methodology used to cluster data and the dimensions measured, allowing the localized distribution to be captured. Based on this review, a clustering approach could be derived that best fits the data for an available geographical location.

METHODS AND MATERIALS

According to Radtke (2022), it's important to use structured methods for unbiasing science. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) scheme was applied for the systematic review (Guba 2008; Fink 2020). As defined by Wikipedia (2022b), PRISMA "is an evidence-based minimum set of items aimed at helping scientific authors to report a wide array of systematic reviews and meta-analyses." PRISMA primarily focuses on the reporting of reviews evaluating the effects of interventions, but can also be used as a basis for reporting systematic reviews with objectives other than evaluating interventions (Moher et al. 2009). Table 1 presents an overview of the research framework.

The search for relevant records was conducted in the mentioned databases from October 10th until October 19th, 2021. The keywords were intended to cover the combination of district heating data and clustering methods. Because today's smart-meter data are almost exclusively electricity-based, the term was excluded, as well as the key word *remote*, which stands in the broadest sense for all processes from a distance. The inclusion criteria were as follows: clustering heating data, which were used in combination with the corresponding dimensions (consumer, consumption vs. peak load, load profile, pattern).

The exclusion criteria were as follows:

- electricity
- estimated values, replacement values, substitute values
- results about stand-alone installations
- geographically originated data except Europe were excluded.

RESULTS

Results of the Search

The number of retrieved materials, according to the search databases, during the defined period is presented in Table 2.

In this systematic review, no publication was excluded due to its type. According to the mentioned PRISMA flow chart (Fig. 1), the following search steps were conducted:

Identification. In this step duplicates were removed, resulting in 821 of 1,615 records remaining in the review process.

Screening. The titles of these records were screened, and 567 were removed due to a missing relation to the research topic. Most of these removed records were in the field of traditional consumption clustering or in energy-related sectors. Based on the overlap of smart meters and smartphone technologies, various records from the field of computer science were found. Those were also rejected due to the lack of connection to the research question. After this step in the review process, 254 publications remained in the database and advanced to the next stage. The abstracts of the remaining records were read, and 187 of them were also eliminated due to irrelevance to the research question.

Eligibility. The remaining 67 records were read in full and evaluated for their use in the systematic revision; 56 were excluded for different reasons. As in the screening phase, some had a wrong setting (i.e., the combination of apps and smart meter data was not given, or the methodology used was based on electrical devices). Afterwards, the references of the papers were screened completely to identify additional records; no further results were discovered.

Included. Initially only 11 papers were identified. Based on the reviewers' comments, 1 more article was reviewed and included into the work. Twelve of the papers were then assigned to the qualitative synthesis and consequently listed with their scientific results in Table 3. They were grouped according to their characteristics into the following sections: (1) consumption-based cluster analysis and (2) demand-based cluster analysis. If several records appeared in the same year, they were arranged according to the

Table 1
Review protocol according to Wohllebe (2020)

Steps	Description
Review question	Which methods are used to cluster measured district heating data – differentiated by dimension?
Literature search	*Sources:* Microsoft Academic, Science Direct, Google Scholar, and BASE. *Search term:* ("clustering method" AND ("district heating" OR "district heat") AND ("data") AND ("consumption-based" OR "based on consumption" OR "demand based" OR "heating capacity" OR "heat load pattern" OR "peak load" OR "load pattern").
Filter criteria	*Type of work:* All types of publications. *Years:* 2010 - 2021.
Exclusions	*By title:* Examination of topics in a broader sense, exclusion of publications especially related to electricity. *By abstract:* Exclusion of articles not related to the combination *clustering* and *district heating.*
Evaluation	*Full-text assessment:* Inclusion of those articles which are engaged with clustering accompanying district heat.

Table 2
Initial number of results of literature search

Search term	Science Direct	Google Scholar	BASE	Microsoft Academic	Results after removing duplicates
("clustering method" AND ("district heating" OR "district heat") AND ("data") AND ("consumption-based" OR "based on consumption" OR "demand based" OR "heating capacity" OR "heat load pattern" OR "peak load" OR "load pattern")	833	153	549	80	821

first letter of the main author. After an initial search that revealed 2,687 hits without any restriction for the year of publication, only the last 11 years were selected and considered for further analysis.

DISCUSSION

Demand-based Clustering

In Calikus et al. (2019), clustering was used to discover heat load patterns in DH networks automatically. A data-driven approach was used. The authors used a 3-step pattern: data preprocessing, clustering, and visualization followed by the K-means algorithm for clustering and removal of abnormal heat load profiles. The clustering is performed by building—which several other researchers have used as well (e.g., Du et al. 2019; Wang et al. 2019). Hourly measured values (taken by smart meters) provide a data-based fundament. The paper provides 3 contributions from the analysis of the heating load behavior of DH customers. The first contribution is a method that enables the clustering of buildings by preserving the shape similarities in their heat load profiles and extracting patterns summarizing the typical behavior in each group. The second is detecting buildings with abnormal heat load profiles (i.e., those that look significantly different from their expected heat load patterns). The third contribution is the identification of buildings with control strategies that are unsuitable for their customer category based on visual inspection and the domain experts' validation of discovered heat load patterns.

There was a question as to whether Le Ray and Pinson (2019) was to be included or excluded, as the work partially contains data measured for electrical consumption. However, the main part of the work included hourly measured heating meter data, and the work was considered relevant. As a result, the clustering methodology, which was always compared to K-means, was enhanced to fit multienergy clustering.

(Sala et al. 2019) included the measured data for (1) two individual homes in an apartment building and (2) the district heating substation of the apartment building, which included 72 homes. The K-means algorithm was applied to cluster the days with similar patterns based on the heating consumption, outdoor temperature, and solar irradiance. Four different classification models were proposed to predict the heating consumption using the clustering results and weather conditions. For individual households, heating consumption was not necessarily dependent on weather conditions due to

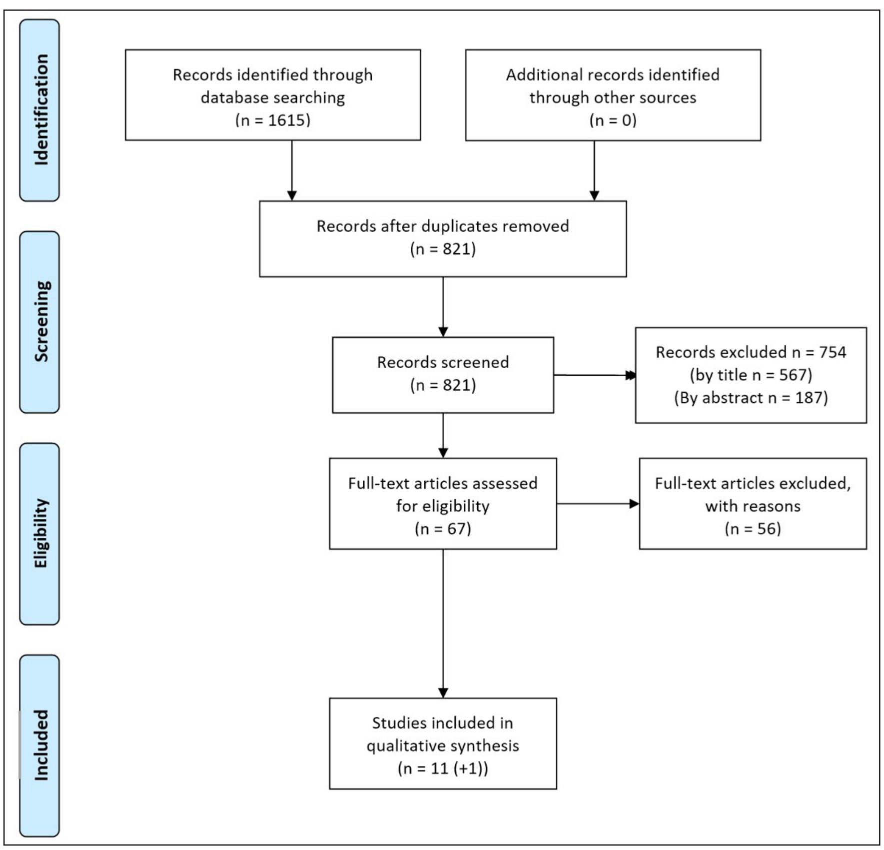

FIGURE 1. PRISMA flow chart

Table 3
Summary of literature review results [a]

Demand-based clustering (measurement in Watt, Kilowatt, Megawatt, Terawatt)		
Author/title	**Key findings and methodology used**	**Geographical origin of data**
(Calikus et al. 2019) A data-driven approach for discovering heat load patterns in district heating	• data-driven approach that enables large-scale automatic analysis of heat load patterns in district heating networks • three step patterns: data preprocessing, clustering, and visualization • K-means algorithm for clustering and removal of abnormal heat load profiles, before re-clustering again • clustering not by household, but by building • hourly measured values (taken by smart meters)	Sweden
(Le Ray and Pinson 2019) Online adaptive clustering algorithm for load profiling	• clustering that consists into an iterative process based on the K-means algorithm that connects time steps • tried to generate 4 slowly changing typical load profiles by using generated profiles taken from ENTSO-E (European Network of Transmission System Operators for Electricity) • the clustering algorithm has been tested on 2 real-world datasets, (1) central district heating loads from 97 buildings in Copenhagen at hourly resolution for a month, (2) 13,241 electrical loads from industries, businesses, and households with PV • for the district heating the consensus clustering is using a modified version of the K-means algorithm • for district heating data RMSE does not depend on the number of clusters and globally decreases over the period • the methodology could be extended to multienergy profiling	Denmark
(Sala et al. 2019) Clustering and classification of energy meter data: a comparison analysis of data from individual homes and the aggregated data from multiple homes	• data used: heating consumption data of 2 different apartments and a district heating substation, as well as the outdoor temperature and solar irradiance • heating substation consists of hourly heating consumption of the apartment building with 72 different households • methodology used 2 approaches: (1) heating data is framed with each day as 1 observation and with hourly data as variables to identify the different daily heating patterns and (2) three different datasets were used, each of them consists of the daily mean value of outdoor temperature, solar irradiance and heating consumption of the apartments and the substation • clustering was done with several algorithms: (1) nbclust() function in R which is equal to K-means, (2) artificial neural network (ANN), (3) decision tree (DT), and (4) Random Forest (RF) • results showed that the models performed differently to the data of 2 individual homes and the data of the substation • for individual households, heating consumption is not necessarily dependent on weather • using data with regular patterns (i.e., heat substation data in this study), the prediction of future trend is reliable and accurate	Denmark

(continued)

[a] The focus is on investigating the clustering methodologies of the publications.

Table 3 (continued)
Summary of literature review results

Demand-based clustering (measurement in Watt, Kilowatt, Megawatt, Terawatt)		
Author/title	**Key findings and methodology used**	**Geographical origin of data**
(Guelpa et al. 2018) Thermal request optimization in district heating networks using a clustering approach	• clustered into 7 groups, clustering is performed through a K-means approach • used the model to simulate the heat flux daily evolution • measures and clustering based on buildings as they tried to respect the thermal conductivity and the inverse of the thermal capacity of the buildings • outcome: optimization is performed by modifying the thermal requests of buildings, anticipating the time the heating systems are switched on (i.e., by virtual storage)	Italy
(Gadd and Werner 2013) Heat load patterns in district heating substations	• clustering depending on the building properties but also of the type of activity that takes place in the buildings • two descriptive parameters: (1) annual relative daily variation and (2) annual relative seasonal variation • different types of reading included: continuous operation control, night setback control, time clock operation control 5 days a week, time clock operation control 7 days a week • 3 conclusions: (1) normal heat load patterns vary with applied control strategy, season, and customer category; (2) it is possible to identify obvious outliers compared to normal heat loads with the 2 descriptive parameters; and (3) the developed method can probably be enhanced by redefining the customer categories by their indoor activities	Sweden
(Goia et al. 2010) Functional clustering and linear regression for peak load forecasting	• focused on peak load, not on average consumption • used hourly observation data • summarized 4 series by plotting the daily mean data, observed a seasonal trend of each period • did not consider weather variables such as temperature, but did use the seasonality trend and did not consider differences between weekdays, weekends, or holidays—as these data were taken for civil residences, values do not change considerably depending on the days of the week • forecast model based on a functional linear regression model which was good for December, January, and February • another model was based on curve classification • evaluated the out-of-sample performances of the functional models	Italy

(continued)

Table 3 (continued)
Summary of literature review results

Consumption-based clustering		
Author/title	**Key findings and methodology used**	**Geographical origin of data**
(Du et al. 2019) Clustering heat users based on consumption data	• two clustering methods: (1) clustering via daily consumption profile, (2) clustering via duration curve • K-means clustering scheme was applied to perform clustering • clustering performed by building	Sweden
(Iglesias and Kastner 2013)	• similarity measures & Euclidean distance • Dynamic Time Warping (DTW) distance • clustered-vector balance is the self-developed and mainly used methodology • FCM clustering → K-means (soft k-means)	Spain
(Tureczek et al. 2019) Clustering district heat exchange stations using smart meter consumption data	• applied learning from smart meter electricity consumption clustering to district heat exchange station clustering • clustering technique K-means on different preparation of data: normalized data, standardized data, mean-centered data, and mean-divided data • additional used: autocorrelation feature extraction and wavelet feature extraction for the cluster performance • data used was gathered by smart meters installed at heat Exchange stations	Denmark
(Wang et al. 2019) New methods for clustering district heating users based on consumption patterns	• data basis: hourly heat consumption readings (in MW) of 561 users (multifamily houses, offices and schools, hospitals and social services) • clustering by GMM (Gaussian Mixture Models) mechanism which is based on a probabilistic model which assumes data points to be generated from a mixture of k (possibly multidimensional) Gaussian distribution • several different ways of clustering were used: (1) modified daily load profile (MDLP), (2) discretized duration curve (DDC), and (3) consumption-production consistency (CPC) • results: almost all user's ambient temperature has strong impacts on the heat demand of all users, discretized duration curve can be used to group DH users, consumption-production consistency can be used to reflect similarity level between DH users	Sweden
(Gianniou et al. 2018) Clustering-based analysis for residential district heating data	• three step patterns: data preprocessing, clustering, and analysis • K-means algorithm (with (for hourly measures) and without normalization (for daily measures)) • segmented the customers into 5 consumption groups • observed seasonal variation • general clustering by households (not by buildings in the first place) • clustering by age of building, area of building, size of households	Denmark

(continued)

Table 3 (continued)
Summary of literature review results

Neither or combined clustering approach		
Author/title	**Key findings and methodology used**	**Geographical origin of data**
(Marquant et al. 2018) A new combined clustering method to analyse the potential of district heating networks at large-scale	• multiple energy systems in a MILP (mixed integer linear programming) problem becomes computationally demanding in terms of solving time when increasing the problem space by augmenting the number of integer variables (exponential increases of the solving time) • multiscale hierarchical approach for DES (distributed energy systems) optimization • a density-based and hierarchical algorithm is employed for clustering • combined electricity and heating • based on 32 buildings, hourly measured heat and electricity data	Switzerland

the high uncertainty and variability in occupants' daily activities and energy use behavior.

Guelpa et al. (2018) clustered their data into 7 groups, and clustering was performed through a K-means approach. The authors used the model to simulate the heat flux daily evolution. They also used measures and clustering based on buildings and tried to respect the thermal conductivity and the inverse of the thermal capacity of the buildings. This also underlined the importance of the usability of historical energy meter data.

Gadd and Werner (2013) drew 3 conclusions from their K-means-based approach: (1) normal heat load patterns vary with applied control strategy, season, and customer category; (2) it is possible to identify obvious outliers compared to normal heat loads with the 2 descriptive parameters; and (3) the developed method can probably be enhanced by redefining the customer categories by their indoor activities.

(Goia et al. 2010) focused on peak load (not on average consumption) and used hourly observation data. They summarized 4 series by plotting the daily mean data and observed a seasonal trend in each period. Interestingly, they did not consider weather variables such as temperature but did use the seasonality trend. Additionally, the authors did not consider differences between weekdays, weekends, or holidays—as these data were taken for civil residences, the values do not change considerably depending on the days of the week.

Consumption-based Clustering

Du et al. (2019) used 2 clustering methods: (1) clustering via a daily consumption profile and (2) clustering via a duration curve. They based the analysis on the K-means clustering scheme. The clusters themselves were based on buildings and not on single households.

(Tureczek et al. 2019) was also almost excluded as they applied learning from smart-meter electricity consumption clustering to district heat exchange station clustering. However, as the study was partly derived from electricity, the work was considered relevant. Their clustering technique was K-means on different preparations of data: normalized data, standardized data, mean-centered data, and mean divided data. Based on the findings earlier from electrical clustering, autocorrelation feature extraction and wavelet feature extraction were used for the cluster performance. Similar to others, the data used were gathered by smart meters installed at heat exchange stations (and not on single households).

Iglesias and Kastner (2013) do not use the K-means algorithm directly, but mainly base their work on similarity measures using the Euclidean distance, Mahalanobis distance, distance based on Pearson's correlation, and Dynamic Time Warping (DTW) distance. Later they base the analysis on fuzzy clustering module that uses the FCM algorithm to compute clusters. The fuzzy c-means algorithm is similar to the K-means algorithm and is rated as an extension to it.

Wang et al. (2019) also used hourly heat consumption readings (in MW) of 561 users (multifamily houses, offices and schools, hospitals and social services). As already seen within the demand-based clustering, authors prefer large buildings or those with combined usage. Single household measurements on an hourly basis are mainly not available for the district heating market. This could be the reason for using combined consumer data. The authors clustered the data by the GMM (Gaussian Mixture Models) mechanism, which is based on a probabilistic model that assumes data points to be generated from a mixture of k (possibly multidimensional) Gaussian distributions. Several different ways of clustering the data were used: (1) modified daily load profile (MDLP), (2) discretized duration curve (DDC), and (3) consumption-production consistency (CPC). They found that almost all users' ambient temperatures have strong impacts on the heat demand of all users, discretized duration curves can be used to group DH users, and consumption-production consistency can be used to reflect the similarity level between DH users.

Gianniou et al. (2018) also used the K-means algorithm for hourly measured data. For single consumer households, the method was applied without normalization. As a result, they segmented the customers into 5 consumption groups. Similar to several others, the authors observed seasonal variations. Uniquely, the general clustering was done by households (not by buildings in the first place). The most interesting part was the clustering by age of building, area of building, and size of household to discover efficiency reserves.

Neither or Combined Clustering Approach

Marquant et al. (2018) combined the clustering. Multiple energy systems in a MILP (mixed integer linear programming) problem become computationally demanding—in terms of solving time—when the problem space is increased by augmenting the number of integer variables (solving time is increased exponentially). They used a multiscale hierarchical approach for DES (distributed energy systems) optimization with a density-based and hierarchical algorithm employed for clustering. Similar to others (Le Ray and Pinson 2019; Tureczek et al. 2019), they used a combined approach to cluster electricity and heating data. However, Marquant et al. used demand-driven and consumption-based data from 32 buildings and hourly measured heat and electricity data.

Conclusions

For the reviewed literature on clustering, mainly the methodology of clustering by K-means is described. The K-means algorithm has been considered to be the best known and most frequently used for clustering, which divides the data set into k clusters by minimizing the sum of all distances to the respective cluster centers (Ramos et al. 2015). Using K-means as a clustering algorithm is well covered by the literature and can serve as a basis for further tests on models and other clustering methods. Several alternative methods have been described and tested, but within the reviewed literature, no common basis for further cluster methods was found. Those researchers who did use an alternative approach always compared their findings to the results of the K-means algorithm. The main difference between the articles is the data basis and the data preparation. Each article used its own set of data—some small (only 2 apartments) up to over 500 measuring places—within district heating (networks); for comparable electricity measures close to 15,000 measuring points were analyzed.

However, this literature review revealed additional differences for those studies that performed a comparative analysis between electricity and heating measures: the influencing factors indicate that the outside temperature (including the geographic region) has a significant effect. The data gathered in Genova showed fewer peaks and less significant differences than the evaluation of data taken in northern Europe (Great Britain or Sweden). The conclusion was rather identical. The most influential factors for volatile consumption were the temperature and the type of building for which the measures were taken. The results did show an effect of modern insolation vs. no insolation at all. However, all researchers adjusted the data, which indicated that consumption remained stable during the period analyzed.

The usage of K-means as a clustering algorithm is mandatory and should not be skipped. Any additional clustering approach must be compared to the results of the K-means method. According to the reviewed literature, the K-means algorithm (which was included in several others such as nbclust(), GMM, FCM, etc.) did show similar results to all other methodologies used. Outliers will have to be respected and treated—but that's the general rule when using the K-means algorithm. The best documented approach according to the reviewed literature is K-means; all other algorithms were only used by single papers, while two-thirds of the papers included statements and results regarding K-means.

When checking the geographical location of the data origin, the coverage of eastern European countries is nonexistent. Even before the functional limitation for heat load and patterns, or even district heating, none of the observed materials were created using data from eastern Europe. Reasons for this could be lack of interest in English speaking research or lack of research interest. The third explanation could be the geographical fixation of publishing journals. This is a research gap.

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SUPPLEMENTAL MATERIAL

Supplemental material to accompany this report is available at: http://hdl.handle.net/1811/102449