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Journal of Statistika | Czech Statistical Office | Na padesátém 81 | 100 82 Prague 10 | Czech Republic
e-mail: statistika.journal@czso.cz | web: www.czso.cz/statistika_journal

PriceIndices – a New R Package for Bilateral and Multilateral Price Index Calculations

Jacek Białek [1] | *University of Lodz, Lodz, Poland*

Abstract

The methodology of price indices dedicated to scanner data is broad, multifaceted, and still contains many open problems. The main challenges include choosing the index formula and the time window width in multilateral methods, as well as determining splicing or other data updating methods. Many NSIs experiment with scanner data, their processing, classifying, matching, and finally using this type of data for CPI calculations. However, these activities are limited, which is partly due to the lack of widely available software in this field. On the one hand, R packages dedicated to price indices are available (e.g. *IndexNumR or micEconIndex*), on the other hand, their functionality and the scope of implemented methods are quite limited. The article discusses a new R package, i.e. *PriceIndices*, which is used to process scanner data and to calculate bilateral and multilateral price indices. The assumptions for the construction of the package were such that it would serve both practitioners and scientists through a multitude of methods and their parameterization. The main purpose of the article is to present the utility of the package in the field of analyzing the dynamics of scanner prices. All obtained results are based on the real scanner data set on milk obtained from one retailer chain in Poland and included in the *PriceIndices* package.[2]

Keywords	***JEL code***
Scanner data, bilateral indices, multilateral indices, elementary indices, chain indices, superlative indices	*C43, E31*

INTRODUCTION

Scanner data, alongside web-scraped data, have recently been a fairly popular alternative source of information in Consumer Price Index (CPI) measurement. The availability of electronic sales data for the calculation of the CPI has increased over the past 18 years. Scanner data mean transaction data

[1] Department of Statistical Methods, University of Lodz, Rewolucji 1905 r. 41, 90-214 Lodz, Poland. E-mail: jacek.bialek@uni.lodz.pl. Also Statistics Poland, Department of Trade and Services, Aleja Niepodległości 208, 00-925 Warsaw, Poland. E-mail: j.bialek@stat.gov.pl.

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that specify turnover and numbers of items sold by GTIN or another bar code and can be obtained from a wide variety of retailers (supermarkets, home electronics, internet shops, etc.). Scanner data contain expenditure information at the item level, which makes it possible to use expenditure shares of items as weights for calculating price indices at the lowest (elementary) level of data aggregation. They provide some additional information about products (such as the following attributes: size, color, package quantity, etc.) which may be useful in aggregating items into homogeneous groups.

Nevertheless, there are many challenges while using scanner data sets. The first group of challenges is connected with data processing, i.e. row scanner data must be cleaned, classified, matched and (optionally) filtered (Loon and Roels, 2018). This is a huge challenge – these stages usually require the use of advanced techniques of multivariate statistics and machine-learning and/or text-mining methods. Sometimes these stages force NSIs to build new IT systems and sometimes additional, separate modules are created in *R*, *Python*, *SAS, Mathematica* or other environments. The second group of challenges concerns choosing the optimal price index formula and the time window width in multilateral methods, determining splicing or other data updating methods. Experiments in this area are somewhat limited, because most statisticians do not have access to the appropriate software or do not have specialist knowledge in computer science to create above-mentioned scripts. Although the methodology for scanner data and multilateral indices is extensive and constantly evolving (see for instance Ivancic et al., 2011; Krsnich, 2014; Griffioen and Bosch, 2016; de Haan et al., 2016; Chessa and Griffioen, 2016; Chessa, 2017; Chessa et al., 2017; Diewert and Fox, 2017; von Auer, 2019; Mehrhoff, 2019; Białek and Bobel, 2019; Webster and Tarnow-Mordi, 2019; Abe and Rao, 2019; Zhang et al., 2019), functionality of available packages for price index calculations and the scope of implemented methods are still quite limited. For instance, in the case of the popular *IndexNumR* package, the only multilateral price index formula which is available in this package is the GEKS index. Moreover, extending the GEKS index is possible by using "only" three splicing methods: movement splice, window splice and mean splice, i.e. the half splice is not available here, along with the FBEW or FBMW methods (see Section 4). Another R package, *micEconIndex*, provides only a small number of bilateral indices, i.e. the Paasche, the Laspeyres and the Fisher indices. There are some other R packages (e.g. *multilaterals* or *productivity*) but still the list of available methods is quite poor and these packages are not strictly dedicated to the scanner data case.

The article discusses a new R package, i.e. *PriceIndices*, which is used to process scanner data and to calculate bilateral and multilateral price indices. The assumptions for the construction of the package were such that it would serve both practitioners and scientists through a multitude of methods and their parameterization. The main purpose of the article is to present the utility of the package in the field of analyzing the dynamics of scanner prices. All obtained results are based on the real scanner data set on milk obtained from one retailer chain in Poland and included in the *PriceIndices* package. Presentation of this package is divided into the following sections: *data processing, bilateral index calculations, multilateral index calculations, extensions of multilateral indices, aggregation* and *index comparisons*.

1 DATA PROCESSING

The released version of the Priceindices package can be installed from GitHub with the command: *install_github("JacekBialek/PriceIndices")* or from *CRAN: install.packages("PriceIndices").* This section discusses the basic package functions for scanner data processing. Technical details are omitted since they can be found in the package documentation. Please note that the package uses monthly unit values as prices and, as a consequence, daily data on prices and quantities are aggregated to one month.

1.1 Data sets included in the *Priceindices* package

This package includes two data sets: artificial and real. The first one, **dataMATCH**, can be used to demonstrate the **data_matching** function and it will be described later (see Section 1.4). The other one, **milk**, is a collection of scanner data on the sale of milk in one of Polish supermarkets in the period from December 2018 to August 2020. It is a data frame with 6 columns and 4 281 rows. The used variables (columns) are as follows: **time** – dates of transactions (Year-Month-Day); **prices** – prices of sold products (PLN); **quantities** – quantities of sold products (liters); **prodID** – unique product codes obtained after product matching (data set contains 67 different prodIDs); **retID** – unique codes identifying outlets/retailer sale points (data set contains 5 different retIDs); **description** – descriptions of sold milk products (data set contains 6 different product descriptions corresponding to subgroups of milk group). The set milk represents a typical data frame used in the package for most calculations and is organized as follows.

Table 1 First six rows of the "milk" data set

Time	Prices	Quantities	prodID	retID	Description
2018-12-01	7.98	6.5	400032	1311	goat milk
2018-12-01	7.98	91.5	400032	2210	goat milk
2018-12-01	7.98	19.5	400032	6610	goat milk
2018-12-01	7.98	15.5	400032	7611	goat milk
2018-12-01	7.98	43.	400032	8910	goat milk
2019-01-01	7.98	4.5	400032	1311	goat milk

Source: PriceIndices R package *<https://CRAN.R-project.org/package=PriceIndices>*

The milk data set contains transaction data on 6 milk subgroups: goat milk, powdered milk, full-fat milk UHT, full-fat milk pasteurized, low-fat milk UHT, and low-fat milk pasteurized.

1.2 Data preparation

Data_preparing is a function for data preparation. This function returns a prepared data frame based on the user's data set. The resulting data frame is ready for further data processing (such as data selecting, matching or filtering) and it is also ready for price index calculations (if only it contains required columns). The resulting data frame is free from missing values, zero or negative prices and quantities. As a result, the time column is set to be *Date* type (in format: 'Year-Month-01'), columns of prices and quantities are set to be *numeric*. If the description parameter is set to TRUE, then the description column is set to be *character* type (otherwise it is deleted). Please note that the **milk** set is an already prepared dataset but let us assume for a moment that we want to make sure that it does not contain missing values and we do not need the description column for further calculations. For this purpose, we use the data_preparing function as follows: `data_preparing(milk, description=FALSE)`.

1.3 Product classification

Advanced machine-learning methods use for product classification so-called *learning trials*. However, this requires the manual assigning of the appropriate COICOP group to product codes. When we have meticulous and accurate product descriptions, we can alternatively classify products based on the words or phrases appearing in their description. This is done by using the **data_selecting** function. The function returns a subset of the user's data set obtained by selection based on keywords and phrases defined by parameters: **include**, **must** and **exclude** (see documentation). For instance, please use `data_selecting(milk, include=c("milk"), must=c("UHT"))` to obtain a subset of **milk** dataset limited to the UHT category (Table 2) or `data_selecting(milk, must=c("milk"), exclude=c("past","goat"))` to obtain a subset of **milk** dataset with products which are not pasteurized and which are not goat products (Table 3).

Table 2 First six rows of the UHT milk subset (*)

Time	Prices	Quantities	prodID	retID	Description
2018-12-01	2.99	113	60010	1311	full-fat milk UHT
2018-12-01	2.29	650	401350	1311	full-fat milk UHT
2018-12-01	2.68	304	402570	1311	full-fat milk UHT
2018-12-01	2.65	137	405419	1311	full-fat milk UHT
2018-12-01	2.99	560	60010	2210	full-fat milk UHT
2018-12-01	2.50	1914	401350	2210	full-fat milk UHT

Note: (*) Available values of description: *"full-fat milk UHT", "low-fat milk UHT".*
Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

Table 3 First six rows of the not-pasteurized and not-goat milk subset (*)

Time	Prices	Quantities	prodID	retID	Description
2018-12-01	19.58	10.5	403249	1311	powdered milk
2018-12-01	19.58	154.5	403249	2210	powdered milk
2018-12-01	19.58	88.5	403249	6610	powdered milk
2018-12-01	19.58	75.0	403249	7611	powdered milk
2018-12-01	19.58	18.0	403249	8910	powdered milk
2018-12-01	69.95	1.0	400033	2210	powdered milk

Note: (*) Available values of description: *"powdered milk", "full-fat milk UHT", "low-fat milk UHT".*
Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

1.4 Product matching

If the user has a dataset with information about products sold but these products are not matched, then the **data_matching** function can be used. In an optimal situation, an input data frame contains the **codeIN**, **codeOUT** and **description** columns (see documentation) which in practice will contain retailer codes, GTIN or SKU codes and product labels, respectively. The **data_matching** function returns a data set defined in the first parameter (**data**) with an additional column (**prodID**). Two products are treated as being matched if they have the same prodID value. The procedure of generating the above-mentioned additional column depends on the set of available variables for matching. In the most extreme case, when the **onlydescription** parameter is set to TRUE (its default value is FALSE), two products are also matched if they have identical descriptions. Other 5 cases differ from each other with regard to the set of considered variables, for instance, the algorithm for product matching when both product codes (internal and external) are available differs from the algorithm when only one of these codes is available (see the package documentation). If the matching process is to compare product labels defined by the **description** column, then the Jaro-Winkler distance measure is used (Jaro, 1989; Winkler, 1990) to compare each pair of character strings. For instance, let us suppose we want to match products from the artificial data set (**dataMATCH**) included in the package (see Table 4). Let us assume that products with two identical codes (**codeIN** and **codeOUT**) or one of thecodes identical and an identical description are automatically matched. Products are also matched if they have one of the codes identical and the Jaro-Winkler similarity measure, calculated for their descriptions, is bigger than the fixed **precision** value, e.g. let us set its level to 0.98. Let us suppose also that we want to match all products sold in the interval: December 2018–February 2019. Using the following command:

data_matching(dataMATCH, start="2018-12", end="2019-02", codeIN=TRUE, codeOUT=TRUE, precision=.98, interval=TRUE), an additional column (**prodID**) will be added to the data frame (Table 5). Now the data set is ready for further processing (e.g. data filtering) and/or price index calculations.

Table 4 First six rows of the **dataMATCH** set before matching

Time	Prices	Quantities	codeIN	codeOUT	retID	Description
2018-12-01	9.416371	309	1	1	1	product A
2019-01-01	9.881875	325	1	5	1	product A
2019-02-01	12.611826	327	1	1	1	product A
2018-12-01	9.598252	309	3	2	1	product A
2019-01-01	9.684900	325	3	2	1	product A
2019-02-01	9.358420	327	3	2	1	product A

Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

Table 5 First six rows of the **dataMATCH** set after matching

Time	Prices	Quantities	codeIN	codeOUT	retID	Description	prodID
2018-12-01	9.416371	309	1	1	1	product A	24
2019-01-01	9.881875	325	1	5	1	product A	24
2019-02-01	12.611826	327	1	1	1	product A	24
2018-12-01	9.598252	309	3	2	1	product A	30
2019-01-01	9.684900	325	3	2	1	product A	30
2019-02-01	9.358420	327	3	2	1	product A	30

Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

1.5 Data filtering

The *PriceIndices* package includes the **data_filtering** function for data set reduction. This function returns a filtered data set, i.e. a reduced user's data frame with the same columns and rows limited by a criterion defined by **filters** parameter (see documentation). If the set of filters is empty, then the function returns the original data frame (defined by data parameter). On the other hand, if both filters are chosen, i.e. *filters=c(extremeprices, lowsales),* then these filters work independently and a summary result is returned. Please note that both variants of *extremeprices* filter can be chosen at the same time, i.e. **plimits** and **pquantiles**, and they work also independently. For example, let us assume we consider three filters for the **milk** data set: **filter 1** is to reject 1% of the lowest and 1% of the highest price changes comparing March 2019 to December 2018, **filter 2** is to reject products with price ratio being less than 0.5 or bigger than 2 in the same time, **filter 3** rejects the same products as filter2 rejects and also products with relatively low sale in compared months. An additional **filter 4** works for each pair of subsequent months from the considered time interval and under the condition that filtering is done for each outlet (retID) separately. The right commands for these filters and their impact on **milk** data set reduction (with 403 and 817 records when no filter is used in comparison of two months and the whole time interval respectively) are presented in Table 6.

Table 6 The impact of filters 1–4 on data set reduction

Type of filter	Command	No. of records after filtering
Filter 1	data_filtering(milk,start="2018-12",end="2019-03",filters=c("extremeprices"),pquantiles=c(0.01,0.99))	378
Filter 2	data_filtering(milk,start="2018-12",end="2019-03",filters=c("extremeprices"),plimits=c(0.5,2))	381
Filter 3	data_filtering(milk,start="2018-12",end="2019-03",filters=c("extremeprices","lowsales"),plimits=c(0.5,2))	180
Filter 4	data_filtering(milk,start="2018-12",end="2019-03",filters=c("extremeprices"),pquantiles=c(0.01,0.99),interval=TRUE, retailers=TRUE)	773

Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

1.6 Additional product characteristics

The *PriceIndices* package includes 10 additional functions providing dataset characteristics. Please note that if the **interval** parameter is set to FALSE, then these functions compare only periods defined by **period1** and **period2** parameters (see documentation). Otherwise the whole time period between period1 and period2 is considered. Table 7 summarizes these functions.

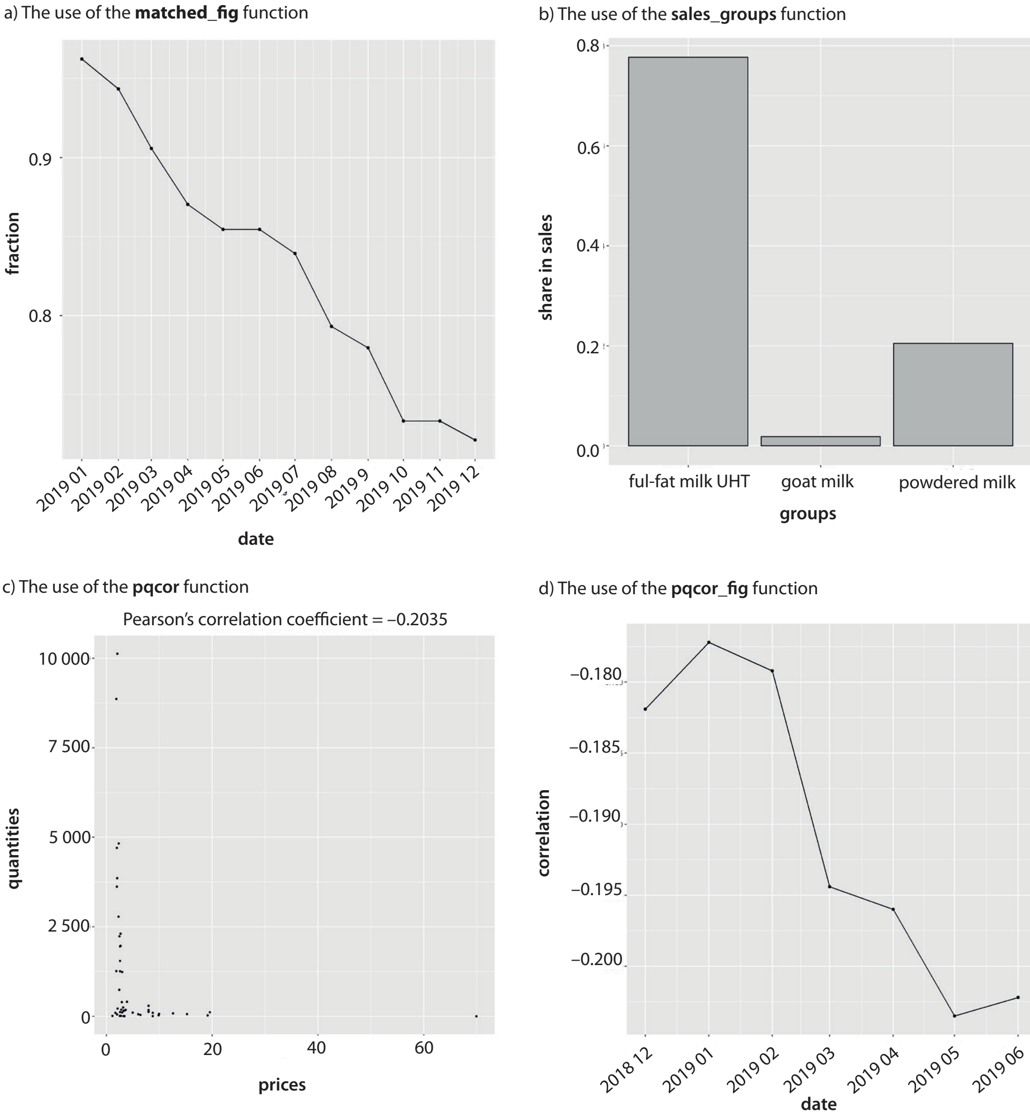
Table 7 Package functions providing dataset characteristics

Function	Description
Available	The function returns all values from the indicated column (defined by the type parameter) which occur at least once in one of the compared periods or in a given time interval. Possible values of the type parameter are: **retID, prodID, codeIN, codeOUT or description.**
Matched	The function returns all values from the indicated column (defined by the type parameter) which occur simultaneously in the compared periods or in a given time interval. Possible values of the type parameter are: **retID, prodID, codeIN, codeOUT or description**.
matched_index	The function returns a ratio of values from the indicated column that occur simultaneously in the compared periods or in a given time interval to all available values from the above-mentioned column (defined by the type parameter) at the same time. Possible values of the **type** parameter are: **retID, prodID, codeIN, codeOUT or description**. The returned value is from 0 to 1.
matched_fig	The function returns a **data frame** or a figure presenting the **matched_index** function calculated for the column defined by the type parameter and for each month from the considered time interval. The interval is set by the **start** and **end** parameters. The returned object (data frame or figure) depends on the value of the **figure** parameter.
prices, quantities, sales	Functions return prices (unit value), quantities and sales (respectively) of products with given IDs (**prodID** column) and being sold in the time period indicated by the **period** parameter. The set parameter means a set of unique product IDs to be used for determining prices of sold products. If the set is empty, the function returns prices of all products being available in **period**.
sales_groups	The function returns **values of sales** of products from one or more **datasets** or the corresponding **barplot** for these sales (if **barplot** is set to TRUE). Alternatively, it calculates the **sale shares** (if **shares** parameter is set to TRUE).
pqcor	The function returns **Pearson's correlation coefficient** for price and quantity of products with given IDs (defined by the **set** parameter) and sold in **period**. If the **set** is empty, the function works for all products being available in **period**. A **figure** parameter indicates whether the function returns a figure with the correlation coefficient (TRUE) or just a correlation coefficient (FALSE).
pqcor_fig	The function returns **Pearson's correlation coefficients** between price and quantity of products with given IDs (defined by the **set** parameter) and sold in the time interval defined by the **start** and **end** parameters. If the **set** is empty, the function works for all available products. Correlation coefficients are calculated for each month separately. Results are presented in tabular or graphical form depending on the **figure** parameter.

Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

For instance, an example of the use of functions: **matched_fig, sales_groups, pqcor**, and **pqcor_fig** (respectively) for the **milk** dataset is presented in Figure 1.

Figure 1 Graphical results obtained by using functions: **matched_fig, sales_groups, pqcor, and pqcor_fig** for the milk dataset (*)



Note: (*) These figures are results of the following package commands: (a) matched_fig(milk, start="2018-12", end="2019-12", type="prodID"); (b) sales_groups(datasets=list(…), start="2019-04", end="2019-07", barplot=TRUE, shares=TRUE); c) pqcor(milk, period="2019-05", figure=TRUE); d) pqcor_fig(milk, start="2018-12", end="2019-06").
Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

2 BILATERAL PRICE INDEX CALCULATIONS

The *PriceIndices* package includes 6 functions for calculating bilateral, unweighted price indices and 24 functions for calculating bilateral, weighted price indices (see Table 8).

Table 8 Bilateral price indices included in the *PriceIndices* package

Unweighted price indices	
Price index formula	Package function
BMW (2007), Carli (1804), CSWD (1980, 1992), Dutot (1738), Jevons (1865), Harmonic	**bmw, carli, cswd, dutot, jevons, harmonic**
Weighted price indices	
Price index formula	Package function
AG Mean (2009), Banajree (1977), Bialek (2012; 2013), Davies (1924), Drobisch (1871), Fisher (1922), Geary-Khamis (1958, 1970), Geo-Laspeyres, Geo-Lowe, Geo-Paasche, Geo-Young, Laspeyres (1871), Lehr (1885), Lloyd-Moulton (1975, 1996), Lowe, Marshall-Edgeworth (1887), Paasche (1874), Palgrave (1886), Sato-Vartia (1976), Stuvel (1957), Törnqvist (1936), Vartia (1976), Walsh (1901), Young	**agmean, banajree, bialek, davies, drobisch, fisher, geary-khamis, geolaspeyres, geolowe, geopaasche, geoyoung, laspeyres, lehr, lloyd_moulton, lowe, marshall_edgeworth, paasche, palgrave, sato_vartia, stuvel, tornqvist, vartia, walsh, young**

Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

To get the chain version of any price index formula presented in Table 8, we need to add "ch" before its name, e.g. **chfisher** is a function for the chain Fisher index calculation (CPI Manual, 2004). Each of these 60 functions returns a value (or vector of values) of the selected bilateral price index depending on the **interval** parameter. If interval parameter is set to TRUE, the function returns a vector of price index values without dates. To get information about both price index values and corresponding dates, we should use general functions: **price_index, price_indices or final_index** (see Section 7). None of these functions takes into account aggregating over outlets or product subgroups (to consider these types of aggregating, we need to use the **final_index** function, see Section 8).

For instance, the following command: **lloyd_moulton**(milk,start="2018-12",end="2019 06",sigma=0.7,interval=TRUE) provides values of the Lloyd-Moulton (CES) index for the month series from December 2018 to June 2019, where the fixed base month is December 2018 and the elasticity of the substitution parameter is set to 0.7. As a result, we obtain the following values: 1.0000000, 1.0155974, 1.0039722, 1.0032047, 1.0029064, 0.9943878, 1.0022053.

3 MULTILATERAL PRICE INDEX CALCULATIONS

This package includes 6 functions for calculating multilateral price indices and one additional, general function (**QU**) which calculates the Quality Adjusted Unit Value index (Table 9).

Table 9 Multilateral price indices included in the *PriceIndices* package

Multilateral price index	**Package function**
CCDI (Caves, Christensen, Diewert, 1982)	**ccdi**
GEKS, GEKS-J (GEKS based on the Jevons index), GEKS-W (GEKS based on the Walsh index) (Gini, 1931; Eltetö and Köves, 1964; Szulc, 1983)	**geks, geksj,geksw**
Geary-Khamis (Geary, 1958; Khamis, 1970)	**gk**
Quality Adjusted Unit Value (de Haan, 2004)	**QU**
Time Product Dummy (TPD) (de Haan and Krsinich, 2017)	**tpd**

Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

The above-mentioned 6 multilateral formulas consider the time window defined by the **wstart** and **window** parameters, where **window** is a length of the time window (typically multilateral methods are based on a 13-month time window). It measures the price dynamics by comparing the **end** period to the **start** period (both **start** and **end** must be inside the considered time window). None of these functions takes into account aggregating over outlets or product subgroups (to consider these aggregating, we need to use the **final_index** function, see Section 8). For instance, the following command:

geks(milk,start="2018-12",end="2019-12",window=13) provides the value of the full-window GEKS index comparing December, 2018 to December, 2012 , i.e. a 13-month time window is used. As a result, we obtain 0.9876098.

4 EXTENSIONS OF MULTILATERAL INDICES

4.1 Splicing methods in the *PriceIndices* package

In the case of bilateral methods, a fixed base month (period) is used and the current period is shifted each month. In monthly c{1,2,...,T}hained index methods, the base and the current month are both moved one month. The problem with proceeding with the next month arises in the case of multilateral index methods. Adding information from a new month may influence values of quality adjustment parameters and values of corresponding multilateral indices. In the literature, we can meet the following window updating methods (or splicing methods): a) *movement splice method* (MS), where a price index for the new month is calculated by chaining the month-on-month index for the last month of the shifted window to the index of the previous month (de Haan and van der Grient, 2011); b) *window splice method* (WS), which calculates the price index for the new month by chaining the indices of the shifted window to the index of *T* months ago (Krsinich, 2014). c) *half splice method* (HS), where the splicing period is chosen to be in the middle of the previous time window (de Haan, 2015); d) *mean splice method* (GMS), which uses the geometric mean of all possible choices of splicing, i.e. all months {1,2,...,*T*} which are included in the current window and the previous one (Diewert and Fox, 2017). All the above-mentioned splicing methods are available in the *PriceIndices* package for any of the discussed multilateral indices (see Section 5). In particular, the following functions can be used: **ccdi_splice, geks_splice, geksj_splice, geksw_splice, gk_splice and tpd_splice**. For instance, let us calculate the extended Time Product Dummy index by using the half splice method with a 10-month time window with the following command (the resulting value is 1.002093):

tpd_splice(milk,start="2018-12",end="2020-02",window=10,splice="half").

4.2. Other extending methods in the *PriceIndices* package

Chessa (2016) proposed a method without using a monthly rolling window. Instead, it uses a time window with a fixed base month every year (December). The window is enlarged every month with one month (*Fixed Base Monthly Expanding Window* – FBEW). Lamboray (2017) proposed a mix of the FBEW method and the *movement splice*. His approach uses a rolling window where the last month of the window is compared to the previous December month. This December plays the role of fixed base, as in the FBEW method. This method is called the *Fixed Base Moving Window* method (FBMW). Both the FBEW and the FBMW methods are available in the package, i.e. to use them for any multilateral price index, we need to add "_fbew" or "_fbmw" to the corresponding index function. For instance, let us calculate the extended TPD index by using the FBEW method using the following command:

tpd_fbew(milk, start="2018-12", end="2020-02"). As a result, we obtain: 0.9977962.

Please note that December 2019 is the chain-linking month here and, following Diewert (2004), the Weighted Least Squares (WLS) method with expenditure shares as weights is used for estimation while calculating the TPD index.

5 GENERAL FUNCTIONS FOR PRICE INDEX CALCULATIONS

This package includes 3 general functions for price index calculation. These functions provide a value or values (depending on the **interval** parameter) of the selected price index formula or formulas. If the **interval** parameter is set to **TRUE**, then it returns a data frame with two columns: **dates** and **index values**. The first two general functions are described as below, the third and the most general function, i.e. **final_index**, is discussed in Section 8:

- **price_index** function.

This function returns a value or values of the selected price index. The **formula** parameter is a character string indicating the price index formula that is to be calculated. If the selected price index formula needs some additional information, it should be defined by additional parameters: **window** and **splice** (connected with multilateral indices), **base** (adequate for the Young and Lowe indices) or **sigma** (for the Lloyd-Moulton or AG mean indices). Table 10 presents an example of the use of the **price_index** function which runs the multilateral Geary-Khamis method for the **milk** dataset, i.e.

price_index(milk,start="2018-12",end="2019-12",formula="gk",interval=TRUE).

Table 10 Results of the use of the **price_index** function in the *PriceIndices* package

Date	gk
2018-12	1.0000000
2019-01	1.0066548
2019-02	1.0008807
2019-03	0.9817312
2019-04	0.9955483
2019-05	0.9918563
2019-06	0.9923588
2019-07	0.9886830
2019-08	1.0001154
2019-09	0.9940940
2019-10	0.9793358
2019-11	0.9779071
2019-12	0.9895014

Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

- **price_index** function.

This is an extended version of the **price_index** function because it allows us to compare many price index formulas by using one command. The general character of this function means that, for instance, one command may calculate two CES indices for two different values of the sigma parameter (the elasticity of substitution) or we can select several splice indices and calculate them by using different window lengths and different splicing methods. Please note that this function is not the most general in the package, i.e. all selected price indices are calculated for the same data set defined by the **data** parameter and the aggregation over subgroups or outlets is not taken into consideration here (to consider it, the **final_index** function should be used – see Section 8). Table 11 presents an example of the use of the **price_indices** function (for the **milk** dataset) which runs the Jevons index, the chain Fisher index, the AG mean index with the elasticity of substitution parameter **sigma**=0.5, the full-window GEKS and CCDI indices and the splicing TPD index, i.e. the TPD index extended by using the *movement splice* method and a 10-month time window, i.e.

```
price_indices(milk,start="2018-12",end="2019-12",
lateral=c("jevons","chfisher"),cesindex=c("agmean"),sigma=c(0.5),
fbmulti=c("geks", "ccdi"),fbwindow=c(13,13),splicemulti=c("tpd_splice"),
splicewindow=c(10),splice=c("movement"), interval=TRUE).
```

Table 11 Results of the use of the **price_indices** function in the *PriceIndices* package

Date	Jevons	Chain Fisher	AG Mean	GEKS	CCDI	Splicing TPD
2018-12	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000
2019-01	1.0227271	1.0021874	1.0161907	1.0020440	1.0018258	1.0034052
2019-02	1.0306252	1.0004589	1.0041815	1.0001378	0.9998011	0.9997846
2019-03	1.0361275	0.9861511	1.0040160	0.9837980	0.9839374	0.9830298
2019-04	1.0076198	0.9943142	1.0033451	0.9935624	0.9931984	0.9949289
2019-05	1.0403077	0.9914703	0.9946718	0.9898290	0.9897645	0.9921140
2019-06	0.9850525	0.9897306	1.0027552	0.9889244	0.9887816	0.9907993
2019-07	1.0053768	0.9875189	1.0034281	0.9861619	0.9863439	0.9860539
2019-08	1.0034188	0.9981165	1.0094286	0.9980918	0.9978275	0.9994174
2019-09	1.0181678	0.9968423	1.0085949	0.9951837	0.9951218	0.9944681
2019-10	1.0248130	0.9784270	0.9838821	0.9774534	0.9771381	0.9789089
2019-11	1.0088363	0.9770267	1.0095095	0.9804598	0.9814365	0.9812340
2019-12	1.0255585	0.9873297	1.0000443	0.9876098	0.9875563	0.9901864

Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

6 FINAL INDEX – AGGREGATION OVER SUBGROUPS AND/OR OUTLETS

All previously presented functions for price index calculation do not take into consideration aggregation over subgroups or outlets. The most general package function, i.e. the **final_index**, returns a value or values of the selected price index taking into consideration aggregation over product subgroups and/or over outlets (retailer sale points defined in **retID** column). If this second option is selected, then for each outlet, i.e. each **retID** code, the set of considered **prodID** codes is limited to those codes which are available simultaneously in all considered months. To be more precise: if both types of aggregation are selected, then for each subgroup of products and for each outlet (point of sale) price indices are calculated separately and then aggregated (according to the aggregation methods indicated) to the form of the final price index. If the **interval** parameter is set to TRUE, then it returns a data frame with two columns: dates and final index values (after optional aggregating). The **datasets** parameter defines the user's list of data frames with subgroups of sold products. The **formula** parameter is a character string indicating the price index formula that is to be calculated. If the selected price index formula needs some additional information, it should be defined by additional parameters: **window** and **splice** (connected with multilateral indices), **base** (adequate for the Young and Lowe indices) or **sigma** (for the Lloyd-Moulton or AG mean indices). The **aggrret** parameter is a character string indicating the formula for aggregation over outlets. Available options are: **none**, **laspeyres**, **paasche**, **geolaspeyres**, **geopaasche**, **fisher**, **tornqvist**, **arithmetic**, and **geometric**. The first option means that there is no aggregating over outlets. The last two options mean unweighted methods of aggregating, i.e. the arithmetic or geometric mean is used. Similarly, the **aggrsets** parameter is a character string indicating the formula for aggregation over product subgroups with identical options as previously. To demonstrate the use of the **final_index** function, let us define four subgroups of milk:

```
g1<-dplyr::filter(milk, milk$description=="powdered milk"),
g2<-dplyr::filter(milk, milk$description=="full-fat milk UHT"),
g3<-dplyr::filter(milk, milk$description=="low-fat milk UHT"),
g4<-dplyr::filter(milk, milk$description=="goat milk").
```

Now, for the fixed time interval: December 2018–May 2019 using the **milk** dataset, let us calculate the (final) chain Fisher price index (the fixed base month is December 2018) taking into consideration the Laspeyres aggregation over subgroups **g1**, **g2, g3, g4** and the Törnqvist aggregation over outlets. The appropriate package command is as follows:

```
final_index(datasets=list(g1,g2,g3,g4), start="2018-12", end="2019-05",
formula="chfisher",aggrsets="laspeyres",aggrret="tornqvist",interval=TRUE),
```

and resulting final price index values are presented in Table 12.

Table 12 The final chain Fisher index calculated for **milk** and with aggregation over subgroups and outlets

Date	Chain Fisher
2018-12	1.0000000
2019-01	1.0021740
2019-02	1.0077480
2019-03	1.0129532
2019-04	1.0089259
2019-05	0.9960455

Source: PriceIndices R package *<https://CRAN.R-project.org/package=PriceIndices>*

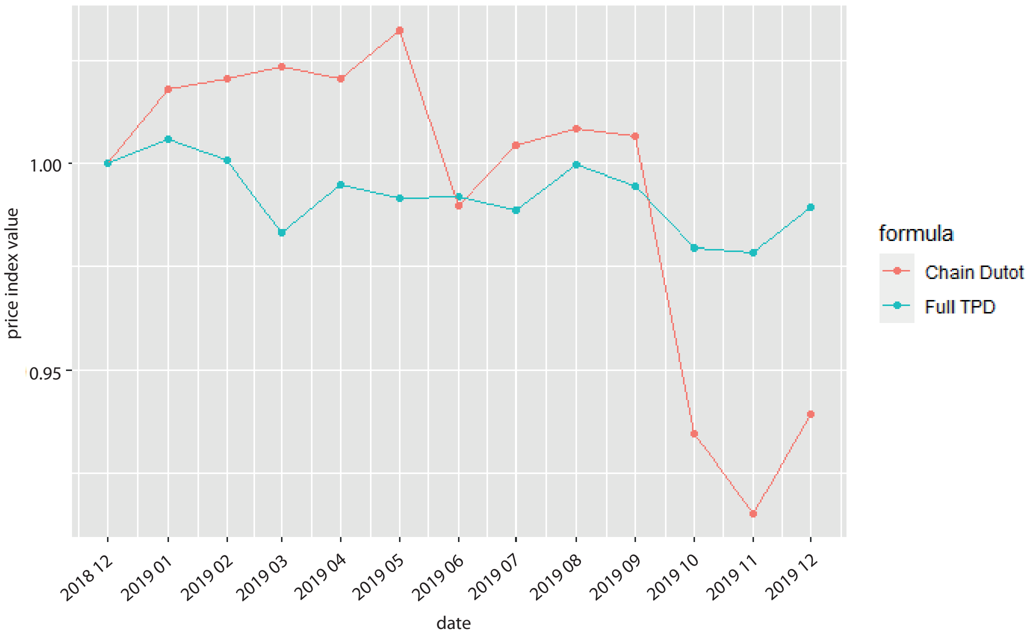
7 GRAPHICAL COMPARISON OF PRICE INDEX RESULTS

This package includes 2 functions for simple graphical comparison of price indices. The first one, i.e. **compare_indices**, is based on the syntax of the **price_indices** function, and thus it allows us to compare price indices calculated on the same data set. This function calculates selected bilateral or/and multilateral price indices and returns a figure with plots of these indices (together with dates on the X-axis and the corresponding legend). The function does not take into account aggregating over outlets or product subgroups. For instance, let us compare the price dynamics for the milk dataset for the time interval: December 2018–December 2019, calculated by using two price index formulas: the chain Dutot index and the full-window TPD index. The above-mentioned comparison can be made by the following command:

```
compare_indices(milk,start="2018-12",end="2019-12",
bilateral=c("chdutot"),fbmulti=c("tpd"),fbwindow=c(13),
namebilateral=c("Chain Dutot"), namefbmulti=c("Full TPD")),
```

and its result is presented in Figure 2.

Figure 2 An example of the use of the **compare_indices** function



Source: PriceIndices R package <*https://CRAN.R-project.org/package=PriceIndices*>

The second function, i.e. **compare_final_indices**, has a general character since its first argument is a list of data frames which contain results obtained by using the **price_index** or **final_index** functions. To be more precise: the **finalindices** parameter is a list of data frames with previously calculated price indices. Each data frame must consist of two columns, i.e. the first column must include dates limited to the year and month and the second column must indicate price index values for the corresponding dates. The above-mentioned single data frame may be created manually in the previous step or it may be a result of the following functions: price_index or final_index. All considered data frames must have an identical number of rows. The names parameter is a vector of character strings describing names of presented indices. For instance, let us compare the impact of the aggregating over outlets and subgroups on the price index results (e.g. the Laspeyres formula is the assumed aggregating method). For this purpose, let us calculate the full-window **GEKS index** in two cases: **case1** without the above-mentioned aggregation and **case2** which considers that aggregation. We use the **milk** dataset and the yearly time interval:

case1<-**price_index**(milk, start="2018-12",end="2019-12",formula="geks", interval=TRUE),

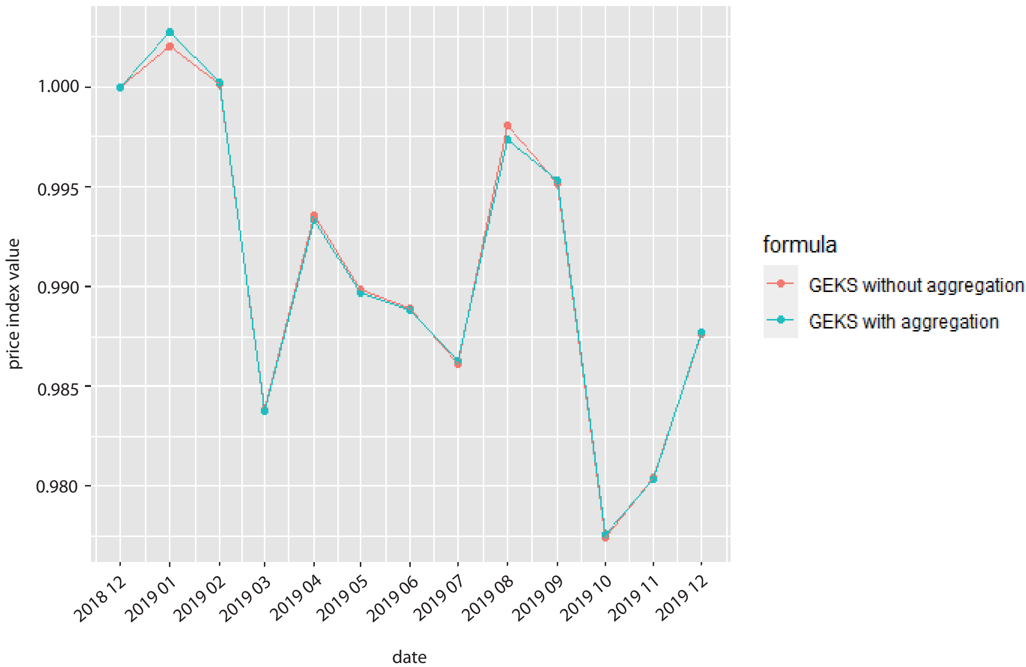
case2<-**final_index**(datasets=list(milk), start="2018-12", end="2019-12", formula="geks", aggrsets="laspeyres", aggrret = "laspeyres", interval=TRUE),

compare_final_indices(finalindices=list(case1, case2),

names=c("GEKS without aggregation", "GEKS with aggregation")).

The results of the above-mentioned comparison are presented in Figure 3. Differences between the calculated GEKS indices are negligible in the case of milk.

Figure 3 An example of the use of the **compare_final_indices** function



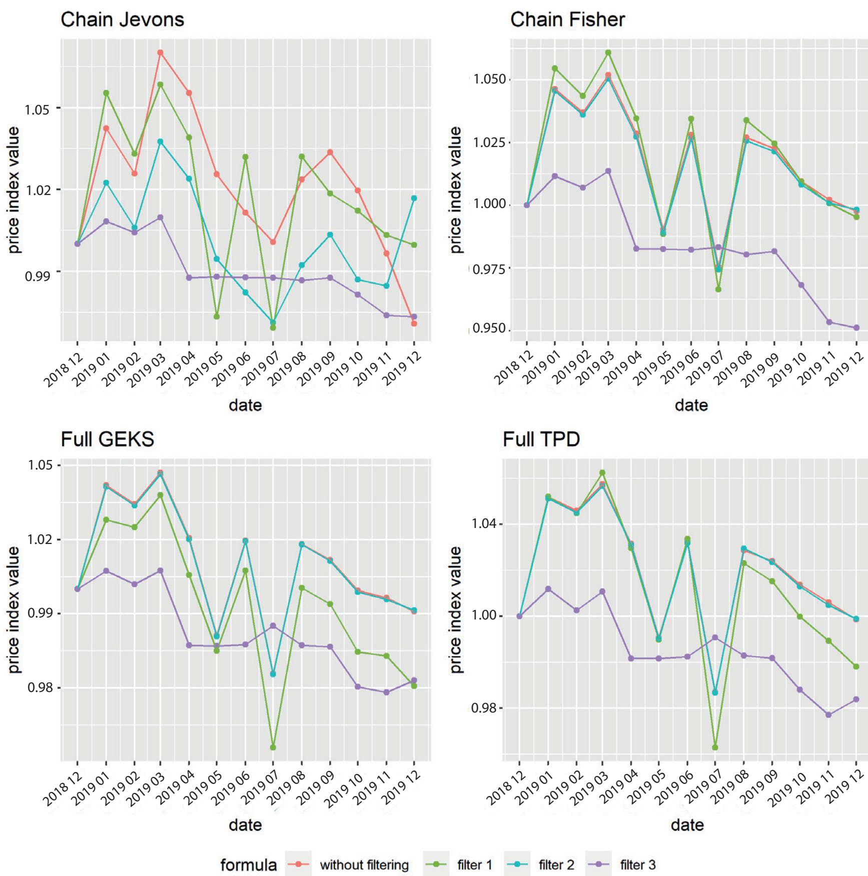
8 AN EXAMPLE OF AN EMPIRICAL STUDY USING THE *PRICEINDICES* PACKAGE

This section examines the influence of the choice of the data filter type on the final price index result. Discussion about whether and what types of data filters to use for scanner data is ongoing in the literature. As a rule, scanner data indices are calculated using a dynamic approach and most countries use the monthly chained Jevons index. This method is commonly named the dynamic method (Eurostat, 2017). The dynamic basket is determined using turnover figures of individual products in two adjacent months, i.e. the product is included in the sample if its turnover is above a fixed threshold being determined by the number of products in the considered product group. In the literature (Van Loon and Roels, 2018), we can meet the following condition for the above-mentioned rule which indicates whether the i-th product is taken into consideration while comparing months $t-1$ and t:

$$\frac{s_i^{t-1}+s_i^t}{2} > \frac{1}{n\lambda}, \tag{1}$$

where s_i^τ denotes the expenditure share of the i-th product at time τ, n is the number of considered products and λ is a fixed parameter (as a rule 1.25). We will call this kind of data filter the *low sale filter*. Supporters of using filters also assume that products that show extreme pricing changes from one month to another should be also excluded from the sample (*extreme price filter*). The list of possible data filters is longer, e.g. Statistics Belgium implements a filter for *dump prices* (van Loon and Roels, 2018). Filtering products is one thing and the decision to proceed with them is another. One possible option is the imputation of prices being flagged by filters but this raises questions about how to impute them. Another option is to remove flagged products from the sample if it does not change the sample size critically. This section examines the impact of the use of *low sale filter* and *extreme price filter* on price index values in the latter option. In the empirical illustration, we use the scanner data set (**milk.RData**) from one of retail chains in Poland, i.e. monthly data from 4 outlets on low-fat UHT milk (COICOP: 01142) sold during the period: Dec. 2018–Dec. 2019. We consider the *low sale filter* with $\lambda = 1.25$ (**filter1**) and the *extreme price filter* with thresholds for the minimum and maximum price change set to 50% and 200% (**filter2**). We use another variant of the *extreme price filter*, namely the filter which rolls out products with price changes (in compared months) being smaller and bigger than the 1th and 99th quantile of all observed price changes (**filter3**). We investigate the impact of the above-mentioned filters on the final price index results where the considered final index formulas are: the chain Jevons, the chain Fisher, the full-window GEKS and the full-window TPD indices. While calculating the final index, we consider aggregation over outlets, i.e. the aggregation is done by using the Törnqvist formula. Please note that filtering is done for each outlet separately, too. The whole procedure of the empirical study can be found in the Appendix. The obtained results are presented in Figure 4.

Figure 4 Impact of the *low sale filter* and *extreme price filters* on the final index value based on the example of **low-fat UHT milk** sold during the period: Dec. 2018–Dec. 2019



Source: PriceIndices R package *<https://CRAN.R-project.org/package=PriceIndices>*

The unweighted Jevons price index formula seems to be the most sensitive to the choice of the data filter. The quantile filter, i.e. the filter 3, seems to influence considered price indices in the same way, namely: as a rule, its use leads to the smallest values of final indices (e.g. the exception month is July, 2019). Presumably, this means that the distribution of monthly price changes is left-sided asymmetrical, i.e. products with larger monthly price changes than the average monthly price change dominate. In the case of weighted formulas (the Fisher, GEKS, TPD), the impact of filter 2 on the price index value is rather negligible. It can be easily justified since we do not observe any extreme price changes in the case of milk observed during the considered time interval. Moreover, differences in price changes between milk products with the biggest and the smallest sale values are probably small but not negligible, i.e. there is a substantial impact of the filter 1 (green line) on the index value observed especially for the chain Jevons and the full-window GEKS indices. In their case, the difference between the index values obtained with and without filter 1 may exceed 2–3 p.p.

CONCLUSIONS AND FINAL REMARKS

The presented R package, i.e. PriceIndices package, was created for both official price statistics and statisticians dealing with theory of price indices. The main assumptions when creating the package were such that, firstly, it would cover the largest set of price indices and methods, and secondly, would be as flexible as possible in controlling parameters related to price index formulas. The author of the package hopes that this is the case: the package contains 104 useful functions for data processing, price index calculations and price index comparisons, including 6 functions for calculating bilateral unweighted price indices, 24 functions for calculating bilateral weighted price indices, 30 functions for calculating weighted and unweighted chain price indices and 6 functions for calculating multilateral price indices. Moreover, the package allows us to extend multilateral price indices by using known and updated methods, i.e. splicing, the FBEW and FBMW methods. According to the best author's knowledge, this distinguishes the PriceIndices package from other packages dedicated to price indices. The package can be useful at any stage of dealing with scanner data: it allows for preliminary classification of products by labels, their matching and data filtering. Users (statisticians, NSIs, others) who have appropriate data frames prepared in the package or earlier by themselves have a variety of price indices and methods at their disposal, which makes it possible to conduct extensive experiments. The package, as part of the R environment, is free of charge and has the ability to be expanded, also by users. The presented version of the package (ver. 1.0) is its first installment (please use *install.packages("PriceIndices")* to install it) and its author expresses the hope that users will contribute to its extension with further useful functions or will improve its speed as well as reliability and find possible errors. The author of the package thanks in advance all users for any comments. It is also planned to constantly expand the package with methods and index formulas that will appear in the literature on an ongoing basis.

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APPENDIX

R procedure for the empirical study with the use of the *PriceIndices* package

```
library("PriceIndices")

library("ggpubr")

#time interval

t1<-"2018-12"

t2<-"2019-12"

#milk subgroup

data<-dplyr::filter(milk, milk$description=="low-fat milk UHT")

#filters

filter1<-data_filtering(data, start=t1, end=t2, filters=c("lowsales"),
lambda=1.25, interval=TRUE, retailers=TRUE)

filter2<-data_filtering(data, start=t1, end=t2, filters=c("extremeprices"),
plimits=c(0.5,2), interval=TRUE, retailers=TRUE)

filter3<-data_filtering(data, start=t1, end=t2, filters=c("extremeprices"),
pquantiles=c(0.01,0.99), interval=TRUE, retailers=TRUE)

#Chain Jevons

CHJ_no<-final_index(datasets=list(data),start=t1,end=t2,formula="chjevons",
aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

CHJ_f1<-final_index(datasets=list(filter1),start=t1, end=t2,
formula="chjevons", aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

CHJ_f2<-final_index(datasets=list(filter2),start=t1, end=t2,
formula="chjevons", aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

CHJ_f3<-final_index(datasets=list(filter3),start=t1, end=t2,
formula="chjevons", aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

fig1<-compare_final_indices(finalindices=list(CHJ_no,CHJ_f1,CHJ_f2,CHJ_f3),
names=c("without filtering", "filter 1", "filter 2", "filter 3"))

fig1<-fig1+ggtitle("Chain Jevons")

#Chain Fisher

CHF_no<-final_index(datasets=list(data),start=t1, end=t2, formula="chfisher",
aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

CHF_f1<-final_index(datasets=list(filter1),start=t1, end=t2,
formula="chfisher", aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

CHF_f2<-final_index(datasets=list(filter2),start=t1, end=t2,
formula="chfisher", aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

CHF_f3<-final_index(datasets=list(filter3),start=t1, end=t2,
```

```
formula="chfisher", aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

fig2<-compare_final_indices(finalindices=list(CHF_no,CHF_f1,CHF_f2,CHF_f3),
names=c("without filtering", "filter 1", "filter 2", "filter 3"))

fig2<-fig2+ggtitle("Chain Fisher")

#GEKS

G_no<-final_index(datasets=list(data),start=t1,   end=t2,   formula="geks",
aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

G_f1<-final_index(datasets=list(filter1),start=t1,end=t2,    formula="geks",
aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

G_f2<-final_index(datasets=list(filter2),start=t1,end=t2,    formula="geks",
aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

G_f3<-final_index(datasets=list(filter3),start=t1,end=t2,    formula="geks",
aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

fig3<-compare_final_indices(finalindices=list(G_no,G_f1,G_f2,G_f3),
names=c("without filtering", "filter 1", "filter 2", "filter 3"))

fig3<-fig3+ggtitle("Full GEKS")

#TPD

TPD_no<-final_index(datasets=list(data),start=t1, end=t2, formula="tpd",

aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

TPD_f1<-final_index(datasets=list(filter1),start=t1,  end=t2,  formula="tpd",
aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

TPD_f2<-final_index(datasets=list(filter2),start=t1,  end=t2,  formula="tpd",
aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

TPD_f3<-final_index(datasets=list(filter3),start=t1,  end=t2,  formula="tpd",
aggrsets = "none", aggrret = "tornqvist", interval=TRUE)

fig4<-compare_final_indices(finalindices=list(TPD_no,TPD_f1,TPD_f2,TPD_f3),
names=c("without filtering", "filter 1", "filter 2", "filter 3"))

fig4<-fig4+ggtitle("Full TPD")

#results

figure <- ggarrange(fig1, fig2, fig3, fig4,

                    common.legend = TRUE,

                    legend=c("bottom"),

                    ncol = 2, nrow = 2)

figure
ggexport(figure, filename = "result.png")

#end of procedure
```

Multichannel Marketing Attribution Using Markov Chains for E-Commerce

Lukáš Kakalejčík [1] | *Technical University of Košice, Košice, Slovakia*
Jozef Bucko [2] | *Technical University of Košice, Košice, Slovakia*
Paulo A. A. Resende [3] | *University of Brasília, Brasília, Brasil*

Abstract

There are plenty of online media that can be used by ecommerce companies in order to drive the revenue. However, use of this media is usually connected to investment into the selected media. From the company perspective, it is wise to evaluate the outcome of these investments in order to choose the best media mix possible. As customers do not usually buy during their first website visit, it is important to monitor their customer journey and assess the value to particular interactions. The objective of this paper is to analyze the data of selected companies using the Markov chains. The data about online customer journeys were analyzed. We found that the Markov model decreases the credit assigned to the channels favored by last-touch heuristic models and assigns more credit to the channels favored by first-touch or linear heuristic models. By using Markov order estimator GDL (Global Dependency Level), we also found that 4th and 5th order was the most suitable.

Keywords

Attribution modeling, multichannel attribution, e-commerce, marketing, order of Markov chain

JEL code

M31, M21, L1, C10

INTRODUCTION

In collective sports, such as football, trainers usually do not rely on single player to win the game. Moreover, the player himself is usually not ready to take a ball and score a goal without the help of any of his teammates. In marketing, it is very similar. Managers usually do not rely on a single marketing channel to deliver outcome they desire. Successful companies (and football teams, too) used to use several marketing channels (players) to deliver. The goal of the team managers is usually evaluating the most useful players; however, most of them understand that scoring a goal is not the only attribute that matters. Some players usually need to acquire a ball and create opportunity for other players to score.

The same applies in marketing. Some marketing channels are great to acquire a potential customers for the first time, while others are great at closing the deal. Approximately 96% of website visitors

[1] Faculty of Economics, Technical University of Košice, Němcovej 32, 040 01 Košice, Slovakia.
[2] Faculty of Economics, Technical University of Košice, Němcovej 32, 040 01 Košice, Slovakia. Corresponding author: e-mail: jozef.bucko@tuke.sk, phone: (+421)556023269, ORCID ID: 0000-0002-0791-1179.
[3] Department of Computer Science, University of Brasília, Brasília, Brasil.

are not ready to purchase a product online during their first website visit (Bulygo, 2012). On the contrary, since the first visit toward conversion (purchase), the visitors move through the process called the buyer journey. This process represents the sequence of the steps taken by customers during move through the phases of awareness, decision-making, and purchase (Roberge, 2015). The modeling of the buyer journey consists of mapping the customer's interaction with the brand aiming to improve these interactions. This process should result in an increase in sales and customer satisfaction (Wang et al., 2015). Through the progress of digital advertising and technological innovations, companies can track digital "footprints" of the customers on a granular level, bringing the knowledge about customer's behavior and measure the impact of displaying the particular marketing channels to the customers on conversions Ghose and Todri (2015), and Smarandache and Vladutescu (2014). Many researchers such as Peterson (2005), Constantin (2014), or Massara, Liu, Melara (2010) have tried to model consumers' behavior to predict their response. Attribution modeling can be considered another point of view on this particular topic.

Companies do not usually rely solely on a single marketing channel to acquire customers. As was mentioned, several marketing channels are used while working in cohesion to accomplish the company's goals. The value of importance should be assigned to each of these channels. Attribution modeling is a set of rules based on which the credit for conversion or purchase is assigned to the particular marketing channels (Clifton, 2015; Shao and Li, 2011). In research (Ferencová et al., 2015), were defined as a problem connected to the evaluation of the utility of marketing channels in the sales cycle. Despite of executed surveys for customers, it is often difficult to determine the channels they interacted with along their journeys. This issue can be solved by using attribution models where each customer touchpoint with the company can be evaluated. Szulc (2013) and Sterne (2017) claim that the use of attribution modeling helps optimize the allocation of marketing budget, support marketing budgeting, ensure more precise planning of marketing campaigns, ensure the accuracy of cost-per-acquisition calculation and help optimize payments to affiliate partners.

In currently available web analytics tools (such as Google Analytics), there are several heuristic models implemented to determine the merits of each marketing channels, for example in (Clifton, 2015; Kaushik, 2011; Shao and Li, 2011):

- last touch model (100% of the credit is assigned to the channel before the conversion),
- first touch model (100% of the credit is assigned to the first channel that customer got in interaction with),
- linear model (an equal amount of credit is assigned over all the channels that customer interacted with during the journey),
- time-decay model (the highest value is assigned to the last channel or campaign, and the assigned value decreases towards the first channel),
- position-based model (40% is assigned to the first and the last interaction, the rest of the credit is distributed evenly across the remaining channels),
- custom model (analyst itself assigns the value to the channels based on his own set of rules).

In Anderl et al. (2014; 2016), Barajas et al. (2016), and Bryl (2016) were reported that the use of heuristic attribution models is not proper for attribution purposes. Barajas (2016) claim that heuristic models assign a value to each displayed and converting channel, however, they ignore hypothetical reaction without a user being in touch with the advertisement. They stated that heuristic models are not data-driven. Anderl (2014) discusses that despite heuristic models are not accurate, the use of more sophisticated attribution approaches found its place in managerial practice. Bryl (2016) claims that heuristic models are not proper for the channel attribution because of their poor quantity, while their selection requires a managerial decision to choose the right one that will be suitable for the company's data.

There have been several studies that offered more data-driven approaches to the attribution to overcome the weaknesses of heuristic models. Yadagiri et al. (2015), Nissar and Yeung (2015) use Shapley value[4] in their non-parametric approach to attribution as a game theory-based model. In his thesis (Rentola, 2014), Rentola used two models: binary logistic regression to classify customers to converters and non-converters (purchasers/non-purchasers), as well as a logistic regression model with bootstrap aggregation. On the other hand, Shao and Li (2011) used bagged logistic regression and a probabilistic model in their study. In their study, (Li and Kannan, 2014) used a hierarchical Bayesian model. Geyik et al. (2015) developed their attribution algorithm MTA (Multi-Touch Attribution) to solve two problems: spending capability calculation for a sub-campaign and return-on-investment calculation for a sub-campaign (more in (Geyik et al., 2015). On the contrary, Wooff and Anderson (2015) offer an attribution mechanism based on the appropriate time-weighting of clicks using the sequential analysis. Hidden Markov Model was used in the studies conducted by Abhishek et al. (2012), and Wang et al. (2015).

We can see many approaches to the attribution, however, we incline to a Markov chain model proposed by Anderl et al. (2014; 2016) discussed in the following parts of our study. Anderl et al. (2014) and the following study by Anderl et al. (2016) use a higher order of the Markov chains model to attribute the value of the marketing channels. They propose that for practical reasons, the 3rd order is the most proficient when calculating the outcome of particular marketing channels. There was further reported that the Markov model meets the following criteria: objectivity, predictive accuracy, robustness, interpretability, versatility, and algorithmic efficiency. Anderl et al. (2016) also stated that heuristic models undervalue display advertising and pay-per-click campaigns, social media, and e-mail activities. On the other hand, Markov chains distribute the value of the channel more evenly. Based on these criteria, we selected Markov chains to be a suitable method for the analysis of our study. We also prefer this method because of the following reasons:

- The export of customer journeys consisting of marketing channels customers used to come to the website before the purchase is among the standard features of Google Analytics that is the most used web analytics tool (Clifton, 2015). This ensures our analysis might be executed broadly by a company of any size and budget.
- Attribution analysis using Markov chains can be easily executed in software The R Project (2019) with couple lines of code using the package ChannelAttribution (Altomare, 2016) and allows users to compare the results in the standard heuristic models. The data exported from Google Analytics almost exactly suit the structure supported by this package.

Based on the abovementioned claims, we choose Markov chains to be a suitable model for our analysis and therefore will be discussed in detail in the forthcoming section.

1 MARKOV CHAIN AND ITS USE FOR ATTRIBUTION MODELING

Formally, a sequence of random variables $\{X_t\}_{t=1}^{\infty}, X_t \in S := \{s_1, \dots, s_m\}$, is a Markov chain of order *r* if, for all $(a_1, \dots, a_{t+1}) \in S^{t+1}$, where *S* is a set of possible states of random variables of X_t. $P(X_{t+1} = a_{t+1} | X_1 = a_1, \dots, X_t = a_t) = P(X_{t+1} = a_{t+1} | X_1 = a_1, \dots, X_{t-r+1} = a_{t-r+1})$ and $r<t$ is the smallest integer to satisfy it. Essentially, this represents that the probabilities related to X_{t+1} depend only on the last *r* events, for all *t*.

In this context, *S* is referred by the state space, a particular sequence $(a_1, a_2, \dots) \in S^{\infty}$ is called by a trajectory, the size of *S* is the length of state-space or number of states, represented by *m*, and the probabilities of $X_{t+1} = a_{t+1}$ considering that $(X_{t-r+1}, \dots, X_t) = (a_{t-r+1}, \dots, a_t)$ are called the transition probabilities represented by the notation[5] $p(a_{t+1} | a_{t-r+1}, \dots, a_t) := P(X_{t+1} = a_{t+1} | X_{t-r+1} = a_{t-r+1}, \dots, X_t = a_t)$.

[4] The Shapley value is a concept from coalitional game theory. Shapley values are used in cooperative games to fairly distribute the "payout" among the features (Molnar, 2020).

[5] Here, we consider that the Markov chain is stationary, i.e., the transition probabilities do not depend on *t*.

A particular state b is absorbing if the probabilities to leave the state are "0", i.e., $p\left(c|a_{t-r+1},\ldots,b\right)=0, \forall c \neq b$ and, consequently, $p\left(b|a_{t-r+1},\ldots,b\right)=1$.

A Markov chain can be represented by an initial probability distribution for the first r steps and the m^{r+1} transition probabilities. When $r = 1$, it is possible to have a graphic representation for the Markov chain. For more details about Markov chains, we recommend Karlin and Taylor (1975).

Anderl (2014) proposes the use of Markov chains on channel attributions, considering the state space S as the states "Start" and "Conversion" combined with the set of marketing channels. In this case, the process $\{X_t\}$ represents the possible customer journeys through these channels. They suggest using a removal effect for attribution modeling. The removal effect is defined as the probability to achieve the conversion from the "*Start*" state if some of the states (s_i) are removed from the model. As the removal effect reflects the change in conversion rate if the given state s_i is removed, the value (or importance) of the given marketing channel can be determined. If N conversions are generated without the particular channel (compared to the number of conversions in the full model), the removed channel determines the change in the total number of conversions (Bryl, 2016). The Markov chain described in this section defines the methodical framework used in our analysis conducted in the following parts of the study.

2 OBJECTIVES AND METHODS

The main objective of this paper is to define the current state of multichannel attribution and, based on the literature, to analyze the customer journey data of selected companies by using the Markov chains. The main objective is decomposed into two partial objectives:

- to determine the current state of use of attribution modeling; to analyze the multichannel paths of a selected companies with the use of Markov chains,
- to propose the most appropriate order of the Markov chain in terms of predictive accuracy and computing efficiency.

The studies by Anderl et al. (2014; 2016) demonstrated that using the Markov chain to analyze customer journeys, it is appropriate to use its third order. In line with these studies, it could be assumed that by the research of the benefit of marketing channels used by e-commerce on the Slovak market, it is appropriate to use the Markov chain of the third order. Accordingly, we formulate the following hypothesis:

H1: We assume that the use of the third-order Markov chain is appropriate in the attribution modeling of the outcomes of marketing channels used by e-commerce stores operating on the Slovak market.

Approximately 20 companies operating on the Slovak market were approached the goal, while for our study, companies selling their products online through an e-commerce store were selected. From the list of the companies, four of them agreed to take part in the study, provided that their business name remains

Table 1 Share of positive answers to job search questions and item-response probabilities

	Company 1	Company 2	Company 3	Company 4
Scope of activity	Distribution of industrial electronic components for industrial production	Retail sale of sporting goods of a wide range	Retail sale of sporting goods with the focus on running and triathlon	Retail sale of food and nutritional supplements
Revenues for 2016 in ths. €	15 561	16 018	308	4 993
Number of employees	50–99	200–249	3–4	20–24
Tracking period of customer journeys	1.4.2016–31.8.2016	1.7.2016–30.6.2017	1.7.2016–30.6.2017	4.12.2016–4.12.2017

Source: Finstat and our own processing anonymous for work purposes. Table 1, however, shows the basic characteristics of the companies based on data from Finstat (2017) (website providing financial information about Slovak companies), which will give the reader an idea of the nature of the business focus and its size.

The data about the customer journeys of e-commerce customers of the analyzed companies were obtained from the analytics platform Google Analytics that businesses use to measure the performance of their websites (e-commerce). The data from the most common conversion journeys (customer journeys) were analyzed using heuristic models and the Markov chain. The data will be analyzed using The R Project for Statistical Computing (2019), using the web analytics platform Google Analytics (2018), and MS Excel from the Microsoft Office Suite (Microsoft, 2016).

3 DATA

The attribution modeling data used in our work were collected from four e-shops (businesses), one of which is focused on the sale of electronic components, two of which are focused on the sale of sportswear, and the last one is focused on the sale of nutritional supplements. For ease of use, we have chosen to export the customer journeys that ended up as a purchase, based on the visits sources from *Top Conversion Paths* report available in the analytics software Google Analytics, while within the individual customer journeys the following sources of visits (marketing channels) could occur:

- **Direct visit:** represents a situation where a user enters the URL of a web page directly into the browser window or visits a web page using a saved bookmark;[6]
- **Organic visit:** represents a situation where a user enters a key phrase in the search engine (Google, Bing, Yahoo, and others), and then clicks on search results to go to the business website;
- **Referral source:** represents a user visit by clicking on a link on another website (the Social network visits are usually not included);
- **Social networks:** represents a user visit by clicking a link on social networks (Facebook, Twitter, LinkedIn, and others);
- **Email:** represents a user visit by clicking on the link in an e-mail delivered to his mailbox;
- **Paid Search:** represents a user visit by clicking on paid search results (e.g., on the Google AdWords platform);
- **Display advertising:** represents a user visit by clicking an ad banner placed, for example, on the Google Display Network;
- **Other:** represents a user visit from a source that was not mentioned above;
- **N/A:** represents a user visit from a source that the analytical system for some reason has failed to identify.

An example of a customer journey looks as follows:

Paid > Direct > Social > Direct > Direct.

Such a customer journey tells that a user visited the website for the first time through a paid search, then came directly to the page by typing the URL into the browser, later clicked through social networks, and purchased on the website after two more visits when he directly entered the URL into a search engine. No higher data granularity was chosen for the comparability of the results with already existing studies. This means that Facebook, Instagram, or Twitter, for example, are considered as one source of visits marked as *Social networks*. Similarly, this applies to the *Banner ad* channel, where the ad platform or placement of the banner ad is ignored.

6 Visitors from mobile apps or offline advertising sources (TVs, billboards, flyers, etc.) may also be considered as direct visits for inappropriately selected or implemented visitor source tracking.

The use of the Markov model allows analysis of the customer journeys that have not ended up with purchases. However, Google Analytics cannot track them without any further technical implementation. As our goal is to provide a platform for performing attribution analysis that will be available to a wide range of businesses regardless of budget and technical skills, we will consider this limitation as a compromise between availability and accuracy of the analysis being conducted. The analysis of shopping paths that have not ended with purchases also has its weaknesses, as it is not possible to determine with certainty whether or not they will end up as a purchase in the future. Therefore, shopping paths (purchases) that are incomplete can mislead and influence the model results and performance.

When selecting companies for the purpose of this study, we conducted the following steps:

1. We identified Slovak ecommerce stores with the majority of online sales compared to offline sales.
2. We gathered contacts where was possible and initiated request for cooperation on this study.
3. From companies that agreed on participation, we analyzed the available data (tracking setup, sample size etc.) and selected the proper companies.
4. We signed non-disclosure agreement with selected companies and obtained the data.
5. As a result, we were able to work with data from four Slovak companies.

To analyze the e-commerce of the electronic component seller, the data included 284 034 customer journeys, with total revenue generated € 7 665 694. The description of customer journeys is summarized in Table 2. Most of the customer journeys will be analyzed regarding the company selling sports nutritional supplements (Company 4), while the highest sales being recorded at the same time. Nevertheless, the lowest average order value was measured for this business, which also results from the nature of the products sold. On the contrary, the highest average order value was recorded for Company 1, which specializes in the sale of electronic components. In this business, however, the highest average and median value of the number of customer interactions with the business website before the purchase was found. We can assume that the average order value is directly related to the length of the shopping path as customers are likely to decide longer to buy the products. However, the problem of the length of a shopping path may be noted for Company 4, where customers are deciding on average for a long time, and its customers only make low-value purchases. A high number of interactions can also result in a higher cost per customer acquisition if this customer journey involves many interactions with paid marketing channels. The lowest median value for the length of the shopping path can be observed in Company 3, which is a good indicator of the accuracy and persuasiveness of the marketing communications used due to the relatively high average order value. In this case, Company 3 can achieve a low cost-per-acquisition and, therefore, achieve a satisfactory return on investment of its marketing communications.

Table 2 Characteristics of the customer journeys entry data

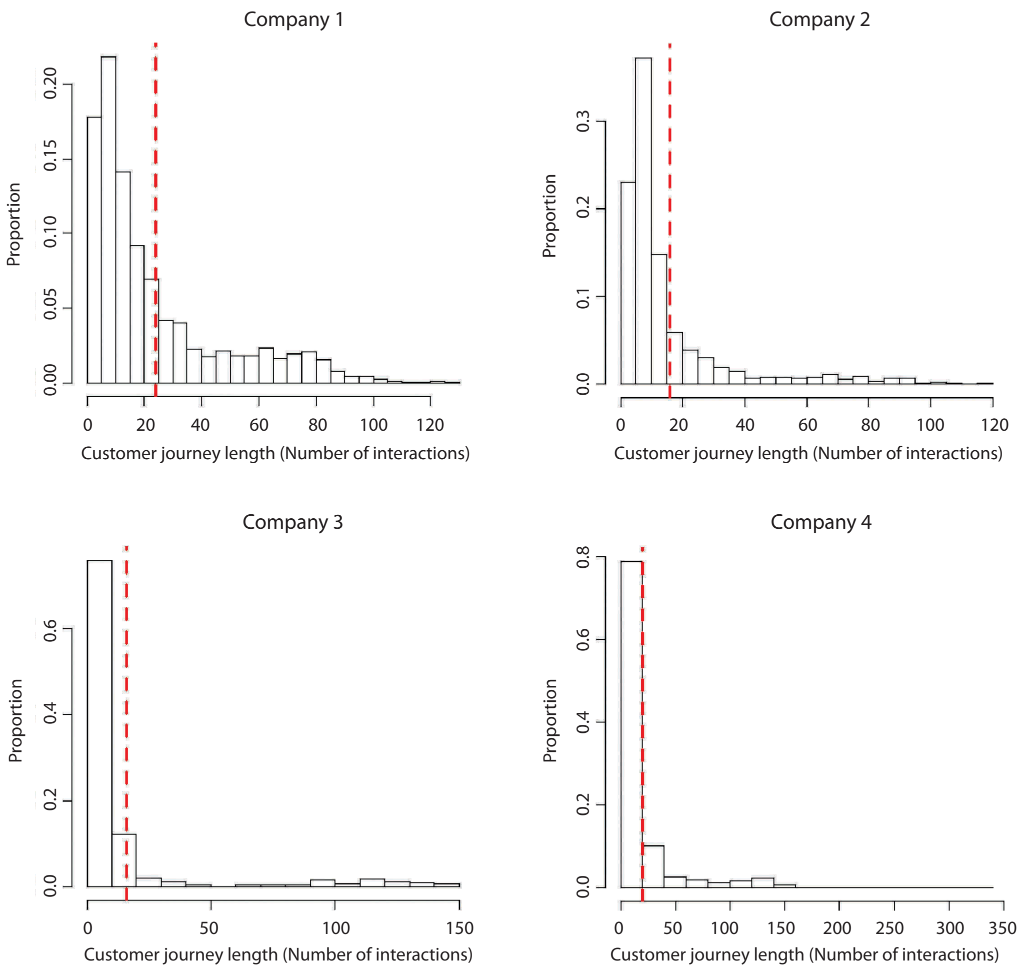
	Company 1	Company 2	Company 3	Company 4
Number of conversions	6 304	21 119	2 118	255 034
Total amount of purchases	1 579 778 €	976 515 €	219 720 €	4 889 682 €
Average order value	250.60 €	46.24 €	103.74 €	19.17 €
Customer journey duration (mean)	23.92	15.72	15.73	20-Feb
Customer journey duration (median)	14	9	6	10

Source: Finstat and our own processing

Figure 1 shows the histograms of the number of interactions in customer journeys per individual analyzed companies. When looking at the histograms, we can say that the distribution of a several customer interactions is positively skewed. This means that most customers choose to buy a product with fewer visits to the website (interactions). Since it was not possible to isolate new and returning customers, we assume that returning customers also have an impact on the skew of this distribution. Another effect may be the inability to monitor a user's activity on multiple devices, for example, when a user can perform product research on a mobile device and then purchase the product on a desktop computer. In this case, such behavior will be recorded as a single-interaction customer journey (if the user did not visit the website on the desktop before making the purchase once again).

In addition to the distribution of customer journeys lengths, it was intended to analyze how this length will affect the revenue generated by businesses.

Figure 1 Customer journey lenght (histogram)



Source: Our own processing

When analyzing the cumulative growth of individual business revenue, it is possible to see that the largest proportion of revenue is generated by customer journeys with fewer interactions. Except for Company 1, where almost 60% of revenue is generated in 20 or fewer interactions in the customer journeys, there is at least 80% of the revenue generated in fewer than 10 interactions. This means that indecisive customers participate in only a small part of total revenue. For business, therefore, a better strategy is to acquire new ("decisive") users than to persuade indecisive potential customers to buy. However, this statement does not apply if these indecisive customers buy repeatedly and decide on the next purchase with fewer visits to the website. As with analyzing the length of shopping paths, the growth of cumulative sales may be distorted by repeating customers and customers buying on multiple devices.

Table 3 Characteristics of the customer journeys entry data

	Company 1	Company 2	Company 3	Company 4
Number of conversions	3 219	16 187	2 118	193 352
Total revenue	463 263 €	736 805 €	219 720 €	3 445 730 €
Average order value	144 €	46 €	104 €	18 €

Source: Our own processing

For the purpose of this study, we were supposed to cover the behavior of new customers, not repeating ones. Therefore, we excluded customer journeys that contained only channel *Direct* from our analysis. This type of journeys might indicate the behavior of repeating customer who already knows the website and therefore visit the website directly. Such customer journeys might affect positively the impact of the channel *Direct* and, therefore, provide us with false assumptions. Table 3 shows the difference in number of conversions, revenue and average order value of analyzed customer journeys without excluded ones.

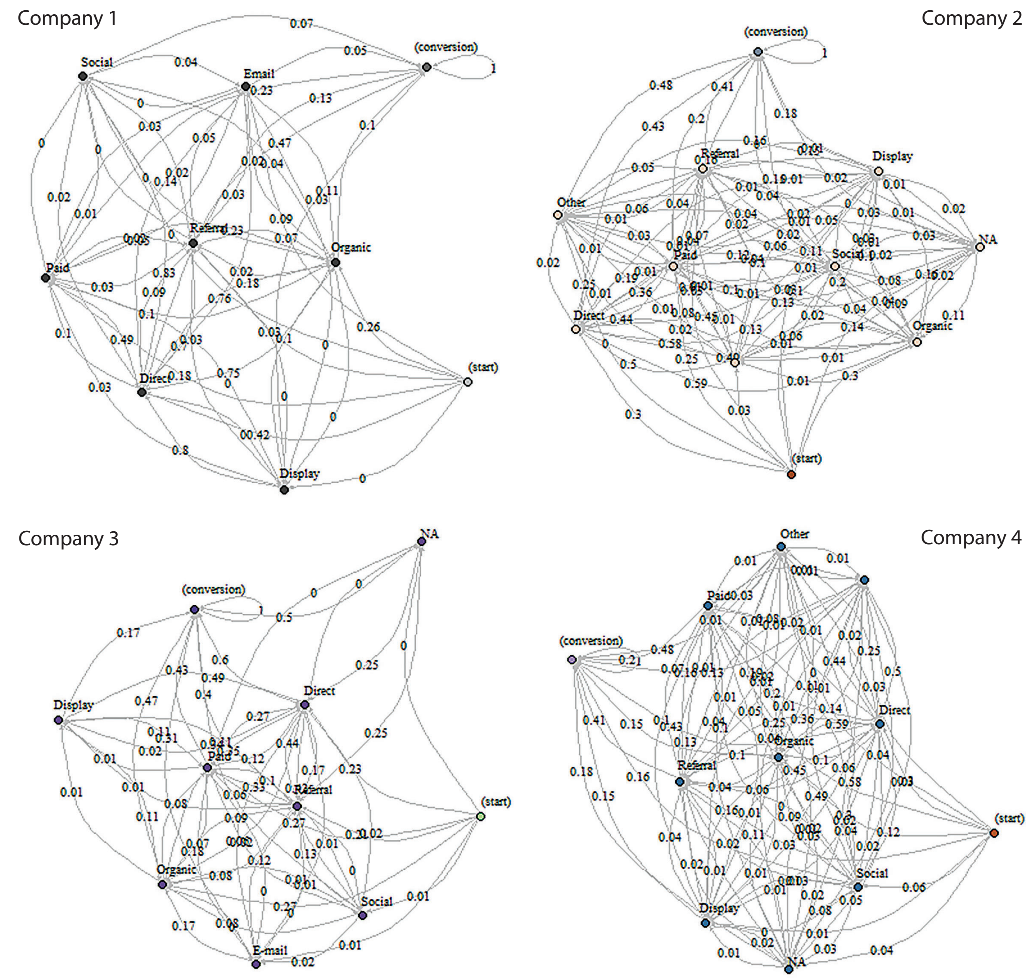
4 THE GENERAL MODEL, CHOICE OF THE APPROPRIATE ORDER OF THE MARKOV MODEL

The Markov model and its application in the customer journey analysis before purchasing products is the content of this part of the study. In the introduction, a basic Markov model of the first order will be applied and the subsequent analysis will focus on assessing the transition probability in the set of determined states defined in the previous sections of the study. This will make it possible to determine which marketing channels can help generate purchases most likely. Subsequently, using the GDL (Global Dependency Level) estimator, which has been mentioned as the most appropriate, an optimal order of the Markov model will be selected. In the last part of this section, the results of attribution modeling of the Markov model of the higher order will be compared with the results obtained using particular heuristic models (first interaction, last interaction, linear model).

In all four analyzed businesses, we were interested in whether there is a greater likelihood that the customer will purchase when using the selected marketing channels. For this reason, the initial step of the analysis was the generation of transition diagrams for each analyzed company. Figure 2 shows the customer journeys transition diagrams for all the analyzed businesses.

The individual points of the graphs represent specific states – marketing channels. It can be noticed that the transition diagram starts with the state *(start)* that represents the start of the customer journey, and ends with the state *(conversion)* that represents the conversion or transaction. Individual states are linked by nodes, each node containing information about the transition probability from a particular state to another particular state. The nodes between the two marketing channels m and n show two probabilities – the probability of transition from state m to state n and the probability of transition from state n to state m. The nodes that connect states *(start)* and *(conversion)* contain only one probability because no customer journey is heading to the state *(start)*. Likewise, no customer journey is heading from the state *(conversion)* towards the marketing channels used. This is a logical state because, after the performed transaction, it does not make sense to monitor what marketing channels the customer uses at the point of further interaction with the business. In the state *(conversion)*, you can see a loop with a pictured probability of 1. This loop originated from computational reasons during the implementation

Figure 2 Transition diagrams



Source: Our own processing

of all the customer journeys. Since all the customer journeys have to go from the state *(start)* to the state *(conversion)*, the loop serves to complete each further interaction until the moment when all the customer journeys from the data file get through the state *(conversion)*.

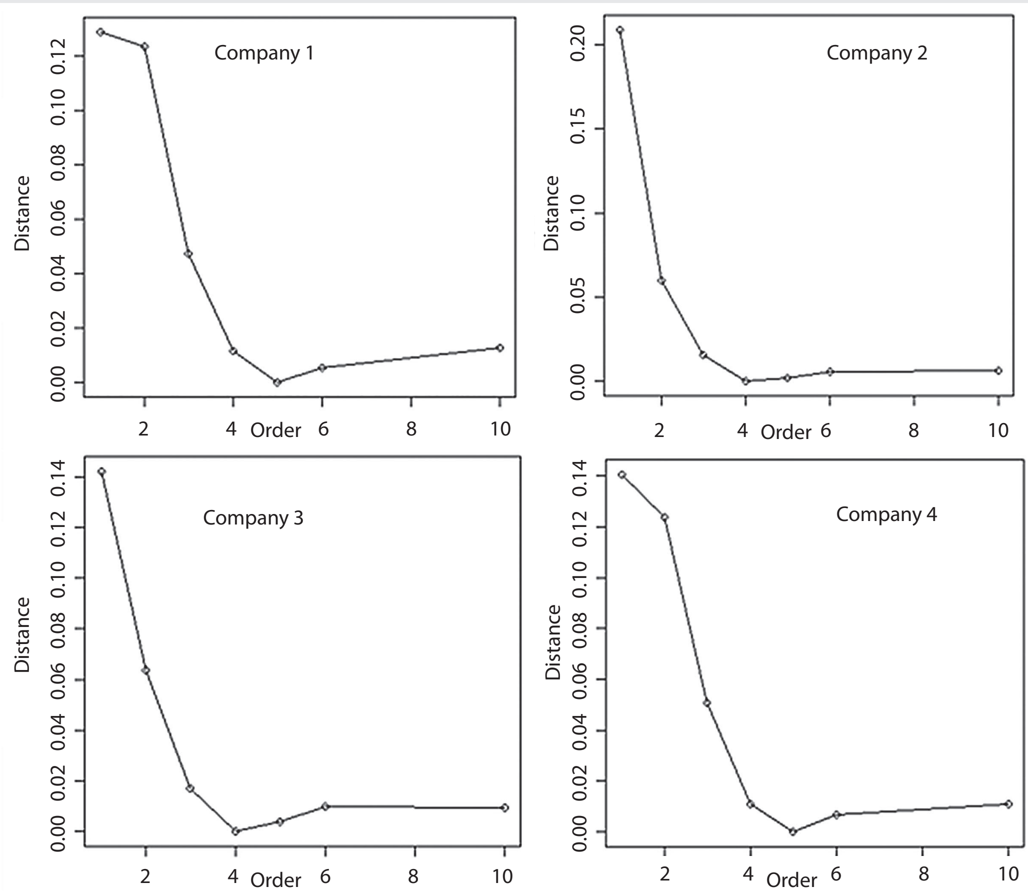
Looking at the heatmaps, it is clear that the analyzed businesses slightly differ in the used marketing channels, but most of them have been used by all the businesses. When analyzing the transition probability, two events can be observed in all four companies:

1. If we do not consider completing a purchase (conversion), with almost every marketing channel, the most likely next step is to visit the website from the *Direct Traffic* source. This means that the result of a positive brand experience when visiting from any source is that customers will either remember the page (and will write a URL directly to the browser on the next visit), or they will save the page as a bookmark to access it later. The positive experience is, therefore, a predictor of increased awareness of the website/brand. This observation is presented as Direct Traffic Effect in study by Kakalejčík et al. (2020).

2. When visiting a website whose source is labeled as *Direct Traffic*, in case of the most of the companies, there is the highest probability that customers will purchase the product. This means that after the customer brand awareness is built, the customer himself will make a purchase when visiting from the *Direct Traffic* source, with the highest probability. Based on this knowledge, a company should strive for the best possible experience during the first customer visits, resulting in a transaction later. In case of Company 3, *Direct Traffic* has the highest transition probability to close the sales, however, the rest of the channels in company's portfolio is similarly valuable.

Within the defined H1 working hypothesis, it was assumed that the first order of the Markov chain used does not represent an accurate representation of the behavior of customers who purchase products online. This supposition continues to work with the assumption that in some cases the customer historically recalls not just an immediate visit to a previous visit to an online merchant's shop during which the customer purchased. In many cases, a customer's memory may exceed the limit of one visit before to the purchase. For this reason, we consider the Markov model of the first order to be irrelevant, while our goal is to set the order that will respond to the customer's behavior the most. Anderl et al. (2016) in their study proved that the use of the third order is the most appropriate for the attribution problem. However, another estimator was used for this prediction.

Figure 3 Markov order (order evaluation)



Source: Our own processing

Figure 3 presents the results of the use of various Markov chain orders, with the criterion for the efficiency of use being chi-square distance when applying the GDL estimator. In this case, the appropriate order is the order in which the local minimum of chi-square distance is achieved. Referring to Figure 3, it is obvious that for Company 1 and 3, the most appropriate order is the fourth order. On the other hand, the fifth order seems to be the most appropriate in the case of Company 2 and 4. It can be seen that the right order when analyzing only new customer varies between 4^{th} and 5^{th}. For practical reasons, however, it can be argued that even with this company the use of the fourth order would fulfill the intended purpose. For the use of the fifth order, it would be necessary to obtain $(9 \times 8)^5$ parameters (almost 2 billions) for a given number of states, but in the case of the fourth order, it is only $(9 \times 8)^4$ parameters (almost 27 millions). The number of parameters directly affects the size of the sample needed for the analysis, as well as the calculation capacity to perform the analysis. Even the transition matrix diverges more when the fifth order is used. So, we concluded that the Markov model of the fourth order might be more appropriate attribution modeling method for e-shops operating on the Slovak market. Based on this finding, we can reject the defined H1 working hypothesis. The result obtained is in contradiction with the result achieved by Anderl et al. (2016).

When analyzing the selection of the appropriate order for the Markov chain, changes in the removal effect were also in the center of our attention. It is established that the higher the removal effect of a given marketing channel, the more important a marketing channel for the business, because excluding it from the marketing portfolio would greatly reduce the number of transactions (conversions) achieved. Table 4 shows the removal effects using the first order of the Markov model in terms of conversions (C), as well as in terms of revenue generated (R).

Table 4 Removal Effects (Markov model of the first order)

	Company 1		Company 2		Company 3		Company 4	
	C	R	C	R	C	R	C	R
Direct traffic	0.90	0.92	0.54	0.60	0.58	0.61	0.81	0.84
Organic search	0.51	0.51	0.51	0.50	0.40	0.37	0.51	0.50
Reference resources	0.19	0.19	0.09	0.36	0.406	0.40	0.16	0.17
Social networks	0.03	0.04	0.07	0.07	0.03	0.03	0.21	0.21
E-mail	0.29	0.30	-	-	0.02	0.02	0.07	0.07
Paid Search	0.37	0.35	0.48	0.50	0.38	0.36	0.50	0.50
Display	0.01	0.01	0.01	0.01	0.02	0.02	0.04	0.03
Other	-	-	-	-	-	-	0.04	0.04
N/A	-	-	0.19	0.20	0.01 <	0.01 <	0.14	0.14

Source: Our own processing

From Table 4 it is obvious that *Direct Traffic* is reaching the highest removal effects, both in terms of conversions and revenue. This knowledge directly supports the findings from the previous part of the analysis which concluded that visits from the *Direct Traffic* channel have the greatest chance of ending up with a purchase. Looking at *Organic Traffic* we can also see relatively high removal effects, which, moreover, are very similar to each of the analyzed businesses. From Table 4, it is also possible to deduct the considerable strength of *Organic search* and Paid *search* and its impact on the number of conversions and sales achieved.

As the testing of the H1 work hypothesis defined the fourth order (Company 1 and 3) and fifth order (Company 2 and 4) as the most effective order in attribution modeling, the analysis of the removal effects using this order was also the focus. The results and percentage differences compared to the first-order removal effects of conversions (C) and generated revenues (R) are shown in Table 5.

Table 5 Removal effects (Markov model of the fourth and fifth order)

	Comp.1 (4th order)		**Comp.2** (5th order)		**Comp.3** (4th order)		**Comp.4** (5th order)	
	C	R	C	R	C	R	C	R
Direct traffic	0.88	0.94	0.62	0.64	0.49	0.54	0.80	0.86
	(−2.7%)	(+2.0%)	(+10.9%)	(+6.4%)	(−15.1%)	(−12.6%)	(−1.4%)	(+1.8%)
Organic search	0.56	0.56	0.50	0.49	0.39	0.36	0.54	0.53
	(+9.2%)	(+9.5%)	(−1.5%)	(−3.1%)	(−1.1%)	(−2.2%)	(+7.5%)	(+6.3%)
Reference resources	0.15	0.19	0.20	0.21	0.31	0.39	0.15	0.18
	(−22.4%)	(−1.1%)	(115.7%)	(+78.6%)	(−15.9%)	(−1.4%)	(−7.9%)	(+7.7%)
Social networks	0.03	0.06	0.07	0.07	0.03	0.03	0.22	0.27
	(+1.8%)	(+71.2%)	(+12.7%)	(+3.9%)	(−6.6%)	(−5.5%)	(−13.5%)	(−0.9%)
E-mail	0.30	0.42	-	-	0.02	0.02	0.07	0.08
	(+3.7%)	(+40.7%)			(−2.6%)	(−9.1%)	(−5.2%)	(+20.2%)
Paid search	0.36	0.35	0.52	0.52	0.33	0.36	0.49	0.46
	(−4.2%)	(−0.2%)	(+7%)	(+2.8%)	(−12.4%)	(+1.3%)	(−0.8%)	(−3.9%)
Display	0.01 <	0.02	0.01<	0.01<	0.02	0.02	0.03	0.04
	(−3.6%)	(+73.8%)	(+6.6%)	(+16.3%)	(−24%)	(−14.8%)	(−13.4%)	(+3.8%)
Other	-	-	-	-	-	-	0.04	0.04
							(−7%)	(−0.2%)
N/A	-	-	0.22	0.23	0.01 <	0.01 <	0.11	0.11
			(+19.3%)	(+13.8%)	(+4.1%)	(+31.9%)	(−18.9%)	(−19.2%)

Source: Our own processing

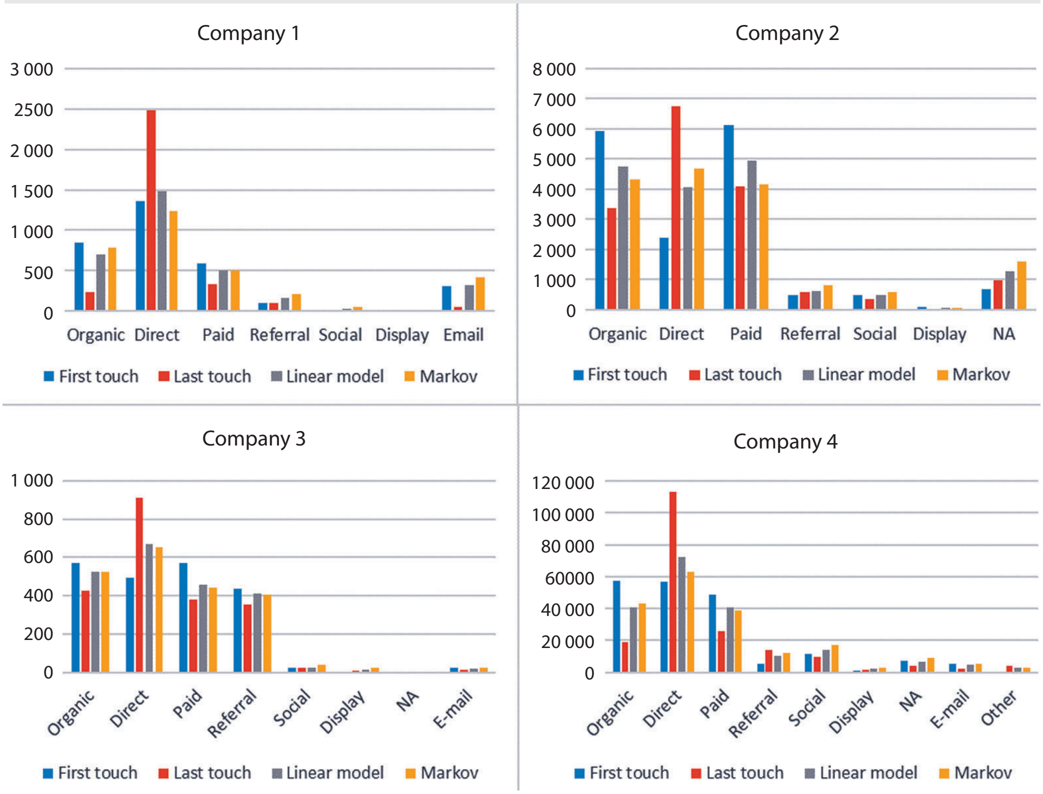
When using the higher order of the Markov chain, it can be noticed that the removal effect after a higher order application changes differently in case of generated conversions compared to the revenue generated. In some cases, the removal effect for the revenue generated increases while removal effect for conversions decreases. This means that, although the dependence of a company on a single marketing channel when selling is lower in terms of the number of conversions generated (as the transition matrix diverges more compared to the first order), the potential loss of revenue value when removing this channel is lower by less percent or, on the contrary, is higher. In other words, despite the lower number of lost conversions, the lost value of revenue would still be high. Therefore, despite the lower significance in the field of transactions obtained, the marketing channel is still of high importance in terms of its contribution to the overall economic result. The subject of analysis should, therefore, emphasize monitoring the removal effects of both attributes, as ignoring one of them may lead to an error in deciding whether or not to use the particular marketing channel.

The last part will focus on the comparison of the Markov model with heuristic models. Figure 4 represents a comparison of the Markov chain and heuristic models, focusing on the distribution of the number of conversions given by the models.

5 ATTRIBUTED NUMBER OF CONVERSIONS BY THE MARKOV MODEL AND HEURISTIC MODELS

As far as the *Direct Traffic* source is concerned, it can be noted that in each of these four cases this source is undervalued by the Markov model in comparison with the heuristic models: the last interaction and the linear model. Since the last interaction model is currently the most used and the linear model represents one of the few multi-touch heuristic models, this finding is significant. The impact of *Organic search* increased, at least compared to last interaction model. In case of Company 1, 2 and 4 *Organic search* also gained compared to linear model, too. In case of *Paid Search*, results are unclear. In case of Company 1, *Paid Search* has gained against each other models. However, in case of Company 2 and 4, it has gained only in comparison with last interaction model and linear model. When comparing the source of traffic *Social Networks*, despite the low number of conversions achieved, it is obvious that the Markov model attributes a higher value to this source than heuristic models. The same situation occurs when comparing the *E-mail* source.

Figure 4 Markov order (order evaluation)



Source: Our own processing

When analyzing the number of conversions of the *Display ad* source, the attributed results were very low. Except for Company 2, where the Markov model was undervalued compared to the first interaction model, the Markov model was assigned a higher number of conversions than all the heuristic models.

Referring to Figure 4, it is also possible to see that conversions mostly depend on 3 basic marketing sources – *Direct Traffic, Organic Search, and Paid Search* (except for referring resources at Company 4, which may have an established network of influencers,[7] and Company 3 which might get a lot of other websites provide links to their website). As a result, a company should strive to be placed as high as possible in the search results for business-related search queries. Also, it should invest in the paid search because it can achieve rapid victories that would not be possible to achieve by the search engine optimization (more in Halligan and Shah, 2014) in a short time. Last but not least, the business should focus on brand awareness as well as a positive user experience when users from other marketing sources are visiting the website. At this point, it is important to add that awareness can also be created by banner advertising, but if the user does not click on the banner but remembers only the brand name or URL of the website, the banner ad will not get a conversion credit (more in the discussion on this part of work).

6 LIMITATIONS AND FUTURE WORK

The results of this analysis can be influenced by factors that could not be taken into account during its implementation. The limitations are as follows:

- **The absence of a NULL state:** the analyzed customer journeys only contain the data about the users who purchased on the website. Clifton (2015), however, discusses that only a small percentage of users (a standard of 3%) purchases in the e-shop. Therefore, the non-inclusion of the NULL state in the analysis can be reflected in the results of the benefits of individual marketing channels. This may also be the reason why Anderl et al. (2016) list the third order of the Markov chain as the appropriate order while we list the fourth order.
- **The impossibility of separating new from returning customers:** we tried to remove repeating customers from our analysis, however, our approach was certainly not accurate. Some of the companies might have offline communications in place (out-of-home communications) and therefore, some of the customers might visit the website directly without previously purchasing on the website.
- **Customer journeys represented the interactions with a website:** the customer could also come into contact with the marketing communication of businesses elsewhere than on the company's website. For example, he could see an ad and not click on it, look at a social network page (e.g., Facebook), and not click on a website, etc. Such behavior was not included in customer journeys.
- **The ambiguity of the *Direct Traffic* source:** the *Direct Traffic* source could represent other marketing channels, e.g. a visit from a mobile app (Facebook, Messenger), a browser bookmark, or an offline ad such as TV, billboards, flyers, or catalogs. Also, each of the analyzed businesses has a brick-and-mortar store.
- **The impossibility of verifying the accuracy of the results obtained:** in contrast to Anderl et al. (2016) or Li and Kannan (2014), it was not possible to test the results of our study using the prediction model, as the Markov model does not allow it. As only the customer data were available, the predictive capabilities of this model might be limited and the model would probably be overfitting and biased. Therefore, the predictive ability of the model must be tested in practical operations.
- **The difference between attribution modeling and setting an optimal budget for the marketing mix:** Danaher and van Heerde (2018) discuss that attribution modeling and budget optimization for the marketing mix are two different concepts. For attribution modeling, the marketing channel that occurred multiple times in the customer journey is attributed to a higher value for conversions/revenue earned. However, this does not mean that the allocation of the marketing budget based on the attribution results does not guarantee its optimal use. Attribution is dependent on exposure and not on costs. Allocating a fixed budget to maximize profits depends primarily on costs, not

[7] Influencer is the user that has an above average impact on other users in the network. For example, a social networking influencer (such as Facebook, Twitter, etc.) is a user who can influence the behavior of other users (Williams, 2016).

exposures. A higher exposure leads to a higher attribution and does not affect on the fixed budget allocation to maximize profits. Higher marketing media costs do not affect attribution but affect fixed budget allocation to maximize the profits. When using the Markov chain for attribution, the exposure of marketing media was reduced if the same marketing medium followed itself in the customer journey at least twice. This method was partly an attempt to eliminate the effect of attribution by exposure.

Although the results of the analysis are limited by the facts described above, it can be noted that only one of these limitations refers directly to the used method. Other limitations exist at the level of analytical software implementation and are associated with the data collection, not analysis. These limitations have arisen because we were not allowed to intervene right into the implementation phase (installation and configuration of the tool) as described in the (Clifton, 2015) four-phase digital analysis process. The added value of the above-mentioned analysis concerns the phase of analytical "adulthood" that is presented in the same process.

When analyzing customer journeys through attribution modeling, future research should consist of the following activities.

- Confirmation of the correct use of the Markov chain of the fourth/fifth order in a wider range of businesses in the Slovak market environment and possible consequences into the European Union markets.
- Removal of the above-mentioned survey restrictions. Priority is to extend the analysis to the customer journeys that do not end with the purchase of the product. Removing this limitation may cause a change in the results of the original analysis performed using the Markov chain.
- Verifying the results obtained during the real operations of the companies that have participated in the study conducted by us.

CONCLUSIONS

Multichannel attribution helps companies assign the value to each marketing channel to select the profitable ones. The main objective of this paper was to define the current state of multichannel attribution and, based on the literature study, analyze the data of the selected companies using the Markov chains. Attribution modeling has already been the focus of the study of several authors.

Based on the works of Anderl et al. (2014; 2016), and Bryl (2016), the Markov chain was used to evaluate the benefit, examining individual customer journeys before the purchase was made. Examined customer journeys came from four e-commerce businesses primarily focused on sales on the Slovak market.

Using the Markov chain, we worked with the assumption that the use of its first order did not correspond to real-world customer behavior. We believe that future customer interaction does not depend only on its current step, but it is influenced by interactions made in the past. Therefore, it is advisable to use a higher order of Markov chain in the analysis. This assumption was directed to the formulation of the H1 hypothesis. The previous work of Anderl et al. (2016) has already pointed out that Markov's third order provides higher accuracy of the model. Our analysis, using the GDL estimator, concluded that it is of the utmost importance for companies operating on the Slovak market to use the fourth and fifth order. This is partly related to the average and median length of customer journeys in the businesses being implemented. H1 hypothesis was therefore rejected. Using the Markov model of the fourth order helped us to uncover another phenomenon that is related to the removal effect of the marketing channel from the portfolio of available marketing channels. With the order growth, the effect of removing individual marketing channels is decreasing, but when looking at revenue, this effect decreases more slowly. This means that, despite of the growing impact of interactions between marketing channels (spillover or carryover effect), removing a given marketing channel from shopping paths will be reflected more significantly in the generated revenues.

At the end of the study, the attribution of the conversions between the newly-formed Markov model and the heuristic models was compared to see if the channel attribution of the conversions differs. When comparing the Markov chain and the heuristic model, the Linear Model (it was chosen for comparison because it considers the entire customer journey as the only one from the monitored heuristic models), it was found that the Markov model attributes a lower value to the selected marketing channels, while attributing a higher value to others.

Although several limitations were identified, we consider the proposed method to be replicable across companies. Each company using Google Analytics can obtain the input data for the proposed model and, therefore, can run the analysis mentioned in this paper. As these companies have an implementation of the software in their control, they can also overcome the limitations we were not able to eliminate.

The methodology and results might be used by companies whose customers need more than one interaction with the company to purchase a product. Moreover, the results and methods can also be used by companies that do not generate online sales to evaluate other types of conversions.

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Ramadan Effect on Prices and Production: Case of Turkey

Cem Eyerci [1] | *Central Bank of the Republic of Turkey, Ankara, Turkey*
A. Ömer Toprak | *Turkish Competition Authority, Ankara, Turkey*
Ömer Demir | *Social Sciences University of Ankara, Ankara, Turkey*

Abstract

The detection of seasonal effects is essential in economic forecasting. However, the lack of indicators produced referencing calendars other than the Gregorian system makes it hard to observe the impact of the cultural, national, and religious days that annually shift in the Gregorian calendar, on the economy. Ramadan, the ninth month of the lunar-based Hijri calendar, has an impact on many issues, namely the Ramadan effect, due to the changes in the daily practices of the fasting Muslim people. We checked the existence of the Ramadan effect on consumer prices and industrial production in Turkey by reconstructing the monthly indicators in the Hijri calendar and testing the significance of the differences between their increase rates in Ramadan and other months. We observed that the Food Price Index and prices of some goods increase, and production decrease in Ramadan, significantly more than in other months. Considering the Ramadan effect would improve the accuracy of the inflation forecasting and seasonal adjustment models.[2]

Keywords	***JEL code***
Consumer prices, Hijri calendar, industrial production, Ramadan effect, seasonal adjustment	*C82, E31, E32, Z12*

INTRODUCTION

Economic life depends on the calendar in various aspects. There are direct seasonal effects on economic indicators such as a decrease in food prices just after the harvest (Gilbert et al., 2017) and mostly in summer, or an increase in energy (Scott, 1995), specifically natural gas (Sailor and Muñoz, 1997; Aras and Aras, 2004) consumption in winter times. Besides, the cultural, national, and religious special days in many societies impact the economic behavior of the majority of the population; the expenditure booms (Scott, 1995; Tremblay and Tremblay, 1995; Al-Hajieh et al., 2011; Strielkowski, 2013) due to gifting, dining, etc. or passenger transportation intensified for increased home travelling (Birg and Goeddeke, 2016) during special days, religious festivals, and holidays.

The detection of seasonal effects is a developed issue in statistics. However, it is worked on much by referencing the Gregorian calendar. Although almost all countries use the Gregorian calendar, various Muslim, Jewish, Hindu, and Chinese societies follow distinct timelines in observing their

[1] Central Bank of the Republic of Turkey (Türkiye Cumhuriyet Merkez Bankası), İstiklal Cad. 10 Ulus, 06050, Ankara, Turkey. E-mail: eyercicem@hotmail.com.

[2] The views expressed in this paper are those of the authors only and not necessarily those of the Central Bank of the Republic of Turkey or Turkish Competition Authority.

religious and traditional days (Riazuddin and Khan, 2005). One of the difficulties in detecting the effects of such days is about the lack of indicators produced on the basis of these calendars or more broadly other than the Gregorian calendar. The lunar-based Hijri calendar that Islamic events follow, for example, includes 12 months of 29–30 days, forming a year of 355 or 356 days, while the Gregorian calendar is solar-based and comprises 365 or 366 days. Thus, the fixed lunar date of an event shifts to an earlier period in the solar calendar each year. Therefore, observing the impact of events moving in the Gregorian calendar requires the reconstruction of the solar calendar-based economic indicators.

Ramadan, the ninth month of the lunar-based Hijri calendar, is considered one of the periods that affect people's lives in many socio-economic aspects. In Ramadan, the expenditure and consumption behavior of Muslim people are expected to be changed due to fasting and related activities. The changes in this month, namely the *Ramadan effect*, may be observed in various fields of social and economic life, such as individual health (Leiper and Molla, 2003; Rouhani and Azadbakht, 2014; Moothadeth et al., 2020), social interactions (Gavriilidis et al., 2016; Haruvy et al., 2018), donation (Martens, 2014), and consumption and production patterns.

In economic aspects, the *Ramadan effect* on stock markets is the most studied issue (Husain, 1998; Oğuzsoy and Güven, 2004; Seyyed et al., 2005; Almudhaf, 2012; Shah and Ahmed, 2014; Küçüksille and Özmutaf, 2015; Sonjaya and Wahyudi, 2016; Gavriilidis et al., 2016; Wasiuzzaman and Al-Musehel, 2018; Iqbal et al., 2019). Ramadan effect on other economy-related fields such as the volatility of economic variables (Yavuz et al., 2008; Ra, 2016), the currency in circulation and deposits (Riazuddin and Khan, 2005; Bukhari et al., 2011), the volatility of deposits (Choudhary and Limodio, 2017), decision making in finance (Demiroglu et al., 2019), loan defaults (Baele et al., 2014), the consumer food expenditure and consumption (Aktaş and Yılmaz, 2012; Moayedi, 2012), demand forecasting (Karabag and Fadıloglu, 2016) and the economic growth and happiness (Campante and Yanagizawa-Drott, 2015) are also studied in the literature.

One of the mentioned effects of Ramadan is its impact on consumer prices, particularly food prices. Since forecasting inflation is essential in monetary policy, besides the regular seasonal effects, any regular "extraordinary" impact on the general price level may be worth considering.

It is widely, but mostly anecdotally, claimed that the food prices increase in Ramadan and in times closer to Ramadan (Yucel, 2005; Bokil and Schimmelpfennig, 2006; Akmal and Abbasi, 2010). If so, it may have various plausible reasons. For example, it is assumed that the demand for food, clothing, and gift items rise in Ramadan (Akmal and Abbasi, 2010). The additional demand gives rise to increase in prices of certain goods and services. Although a comprehensive consumption data is not available, some local works denote that demand for some goods is rising in Ramadan. Aktaş and Yılmaz (2012), for example, found by using a household survey, that the food expenditure in Mersin, a province in Turkey, increased by 10% in Ramadan 1432 (the year 2011 of the Gregorian calendar). Traditionally, people tend to spend more in Ramadan for some foods (e.g., meat) that not always consumed.

On the contrary, the suppliers may increase the prices of certain goods due to their previous years' experience, well before the emergence of the demand. However, when the increase in demand is predicted, it should be expected that the supply would also increase, repressing the rise of prices. Even the prices of some over-supplied goods may decrease in the second half of Ramadan.

On the other hand, Ramadan is expected to affect the industrial production of the related month. Like many other indicators, the production indices are also seasonally adjusted to enable periodical comparisons. Considering the effects of social, cultural, and religious events and periods in seasonal adjustment methodologies, besides the accustomed seasonal structure (Demirhan, 2011) based on the Gregorian calendar, may improve the accuracy of the adjustments. Such that, Demirhan (2011) found the production to decrease in Turkey in Ramadan.

In this paper, we evaluate the Ramadan effect on consumer prices and industrial production in Turkey by using official statistics. In Section 1, the methodology of the work is presented. The raw data and reconstructed price and production indicators for the Hijri calendar are introduced in Section 2. In Section 3, the outcomes of the analysis are summarized and discussed. Finally, the last section of the paper is the conclusion.

1 METHODOLOGY

As mentioned in the previous section, although there are well-developed seasonal effect detection methods, the lack of indicators produced grounding on non-Gregorian calendars prevents us from using some standard methods or decreases their efficiency. That's why researchers use modified or alternative approaches to observe the effect of the cultural or religious days shifting in the Gregorian calendar such as Ramadan.

In almost all works made for *Ramadan effect* analysis, time series methods, mostly the ARIMA model, are used. Riazuddin and Khan (2005), and Yucel (2005) applied the ARIMA model to the Gregorian calendar based data by adding dummy variables for some Hijri months to observe their effect on the currency in circulation and consumer food prices, respectively. The approach obtained to detect the combined impact of seasonality in the Gregorian calendar and Ramadan of Hijri calendar. Yucel (2005) applied the model not only to the data of the Gregorian calendar but to the indicators transformed into the Hijri system. Akmal and Abbasi (2010) also used the ARIMA model with dummy variables to evaluate the Ramadan effect on the consumer price index in addition to graphical and scenario analyses. Hossain, Bashar and Haque (2018) used ARIMA and the Unobserved Components Model (UCM) to investigate the Ramadan effect on the raw sugar price.

Karabağ and Fadıloğlu (2016) claimed that the existing methods, ARIMA, for example, were insufficient to concurrently detect the effects of the climates of the solar year and the cultural seasonality of the lunar year. Therefore, they applied the extended Winters' (1960) method to observe the Ramadan effect on beer demand. Ozmen and Sarikaya (2014) used a different methodology in the analysis of the Ramadan effect on food prices. They estimated monthly inflation equations of food price sub-indices and tested the significance of the variables defined as the number of the Ramadan days corresponding to each month. Demirhan (2011) utilized an alternative time series based model, TRAMO-SEATS, to observe the Ramadan effect on production.

However, the results of the analyses do not imply the same effect of Ramadan. In particular, the ARIMA model applied to consumer prices gave inconsistent results. Yucel (2005), and Akmal and Abbasi (2010) did not observe any Ramadan effect in their works done by the use of data based on the Gregorian calendar. On the other hand, in his analysis of data transformed into the Hijri calendar, Yucel (2005) found that there is a considerable increase in food prices in Ramadan.

The approach of our work is a quite different and less complicated than other methods used in the detection of the Ramadan effect on consumer prices and industrial production. The methodology is composed of the following steps:

(i) The monthly price (3 indices and prices of 43 items) and production (3 indices) indicators that are constructed following the Gregorian calendar transformed to indicators of the months of Hijri calendar.
(ii) The monthly increase rate of each indicator for Hijri months is calculated, and the mean of the increase rates of each indicator is calculated for 12 Hijri months.
(iii) The mean of the increase rates in Ramadan months for each indicator is checked, whether it is the highest or lowest among the means of 12 months.
(iv) The means of indicators in Ramadan months that seem higher than the means of the remaining 11 months are tested for significance by the use of hypothesis testing procedure with:

H_0: $M_{Ram} > M_{others}$,
H_1: $M_{Ram} \leq M_{others}$.
Similarly, the means that seem lower are tested by:
H_0: $M_{Ram} < M_{others}$,
H_1: $M_{Ram} \geq M_{others}$,
where M_{Ram} is the mean of increase rates in Ramadan months and M_{others} is the mean of increase rates in the remaining 11 months.

(v) The tests are repeated for price indicators of Shaban, the 8th month, Shawwal, the 10th month, and the combined three months, Shaban, Ramadan, and Shawwal.

2 DATA

The monthly price and production indicators transformed into the Hijri calendar from the officially produced and disseminated Gregorian calendar based series are used in the analyses.

The original price data is comprised of 3 indices and prices of 43 items (Table 1) disseminated by the Turkish Statistical Institute (TURKSTAT) used in the production of the consumer price index (CPI). The data is available from May 1994 to August 2019 that corresponds to the period from last month of 1414 to the last month of 1440 in the Hijri calendar and provides a series of monthly price increase rates of 26 complete Hijri years (1415–1440).

Table 1 The Indices and Items Included in the Analysis

The Consumer Price Index and Sub-Indices

1	Consumer Price Index (Ind_CPI)
2	Food Price Index (Ind_Food)
3	Clothing and Footwear Price Index (Ind_Clothing-Footwear)

Selected Consumer Items* (Prices)

Food		*Food*		*Alcoholic beverages*	
4	Rice	20	Corn Oil	34	Raki
5	Wheat Flour	21	Tomato	35	Whisky
6	Bread	22	Onion	36	Wine
7	Dessert	23	Potato	37	Beer
8	Veal	24	Dry Bean		
9	Mutton	25	Chickpea	*Clothing and footwear*	
10	Poultry	26	Lentils	38	Men's Trousers
11	Garlic-Flavored Sausage	27	Olive	39	Skirt
		28	Granulated Sugar	40	Women's Trousers
12	Milk	29	Cube Sugar	41	Men's Footwear
13	Yoghurt			42	Men's Sport Shoes
14	White Cheese	*Non-alcoholic beverages*		43	Women's Footwear
15	Kasar Cheese	30	Tea	44	Women's Sport Shoes
16	Egg	31	Carbonated Fruity Beverages		
17	Butter			*Others*	
18	Olive Oil	32	Coke	45	Bus Fare (Intra-Urban)
19	Sun-Flower Oil	33	Fruit Juice	46	Airplane Fare

Note: * The prices of some items were disseminated in breakdown of sub-items for the base year 1994 = 100. The sub-items that are used in linking the prices are listed in Table A1 in the Annex.
Source: Authors' selection from TURKSTAT data

The data is composed of two successive series: 1994 = 100 base year CPI for years 1994–2004 and 2003 = 100 base year CPI for years 2005–2019. Two series are linked by the use of the monthly increase rate in January 2004.

The production data includes three sub-indices of TURKSTAT's Calendar Adjusted Industrial Production Index (IPI). The analyzed indices of one digit NACE Rev.2 (Statistical Classification of Economic Activities in the European Community, Revision 2) activities are B-Mining and quarrying, C-Manufacturing, and D-Electricity, gas, steam and air conditioning supply. The monthly indices and increase rates for 34 Hijri years (1407–1440) are transformed from the 2015 = 100 base year IPI of the period from August 1986 to August 2019.

2.1 Transformation of the data into the Hijri calendar

Although many works on the Ramadan effect were carried out using the original domain of the data, i.e., the Gregorian calendar, some analyses were made by transforming data into the Hijri calendar in the literature. Yucel (2005) reconstructed the Hijri data (monthly increase rates of food price index) by summing up the weighted increase rates of corresponding original monthly food price data of Turkey. Riazuddin (2012) proposed a method for calendar transformation and produced the Hijri CPI of Pakistan.

The method used in this work for the transformation of indicators, namely the reconstruction of the Hijri series, assumes that the price level is stable within each Gregorian month, and the production made in each day of a month are equal. The Hijri indicator is defined for price data as:

$$HX_{im} = \frac{1}{h_{im}} \sum_{n} \sum_{j} GX_{jn}\, n_{im,jn} \,. \tag{1}$$

It is defined for production data as:

$$HX_{im} = \sum_{n} \sum_{j} GX_{jn}\, n_{im,jn} \frac{1}{g_{jn}} \,, \tag{2}$$

where:

HX_{im} : indicator for Hijri month i of year m;

GX_{jn} : indicator for Gregorian month j of year n;

h_{im} : number of days of i^{th} Hijri month of year m;

g_{jn} : number of days of j^{th} Gregorian month of year n;

$n_{im,jn}$: number of days in i^{th} Hijri month of year m corresponding to j^{th} Gregorian month of year n.

The transformation of the CPI that is produced following the Gregorian calendar to seven months of the Hijri calendar is exemplified in Table 2.

The Hijri calendar used in Muslim societies is not unique due to the disputes at the beginning of months. Since the data used in this work is of Turkey, the lunar period of Ramadan that the work based is defined following the calendar declared by the Presidency of Religious Affairs of Turkey (DİB, 2020). The first day of each Hijri year and its corresponding Gregorian date are listed in Table A2 in the Annex.

The graphs of the original and transformed series of two indicators, CPI and the Manufacturing Production Index, are in Figures A1–A4 in the Annex.

Table 2 Example of Calendar Transformation of CPI to Seven Hijri Months

Hijri months			Corresponding Gregorian months				CPI-Original Gregorian)	Partial Effect	CPI-New (Hijri)
Year	Month	Number of days of month	Year	Month	Correspon-ding dates	Number of correspon-ding days			
(m)	*(i)*	*(h_{im})*	*(n)*	*(j)*		*($n_{im,jn}$)*	*(GX_{jn})*	*(GX_{jn}/ h_{im}*$n_{im,jn}$)*	Sum of partials
1414	12	30	1994	5	12–31.05.1994	20	1.144	0.763	1.152
			1994	6	01–10.06.1994	10	1.167	0.389	
1415	1	29	1994	6	11–30.06.1994	20	1.167	0.805	1.178
			1994	7	01–09.07.1994	9	1.203	0.373	
1415	2	29	1994	7	10–31.07.1994	22	1.203	0.913	1.211
			1994	8	01–07.08.1994	7	1.237	0.299	
1415	3	30	1994	8	08–31.08.1994	24	1.237	0.990	1.253
			1994	9	01–06.09.1994	6	1.314	0.263	
1415	4	29	1994	9	07–30.09.1994	24	1.314	1.087	1.330
			1994	10	01–05.10.1994	5	1.409	0.243	
1415	5	30	1994	10	06–31.10.1994	26	1.409	1.221	1.421
			1994	11	01–04.11.1994	4	1.499	0.200	
1415	6	29	1994	11	05–30.11.1994	26	1.499	1.344	1.510
			1994	12	01–03.12.1994	3	1.604	0.166	

Source: Authors' calculation

3 ANALYSIS AND DISCUSSION

3.1 Consumer price in Ramadan

The means of monthly increase rates of prices in 26 Hijri years (1415–1440) are listed and ranked (see Table A3 in the Annex). The indices and prices with the first and second, highest and lowest means of increase rates (ranks of 12, 11, 1, and 2 respectively) in 9th month Ramadan, the previous month Shaban, and the next month Shawwal (Table 3) are distinctly tested for having means of monthly increase rates higher or lower than the means of the remaining months. The term "Coresponding" should be deleted and the fallowing should be a new paragraph.

CPI and prices of four items increased most on average in Ramadan (Table 3). The means of the increase rates of prices of three items (*Milk, Mutton, Veal*) are significantly higher than the means of other months (see Table A4 in the Annex). However, the difference in the increase rates of *CPI* and price of *butter* in Ramadan and in other months are not significant. On the other hand, although the means of the increase rates of the prices of *chickpea* and *Women's Sport Shoes* decreased most on average in Ramadan, they are not significantly lower than in other months. The monthly means of increase rates of selected nine prices are graphed in Figure 1, and the monthly distributions of increase rates of selected three prices are graphed in Figure 2.

Table 3 The price indicators with highest and lowest increase rates in Shaban, Ramadan, and Shawwal

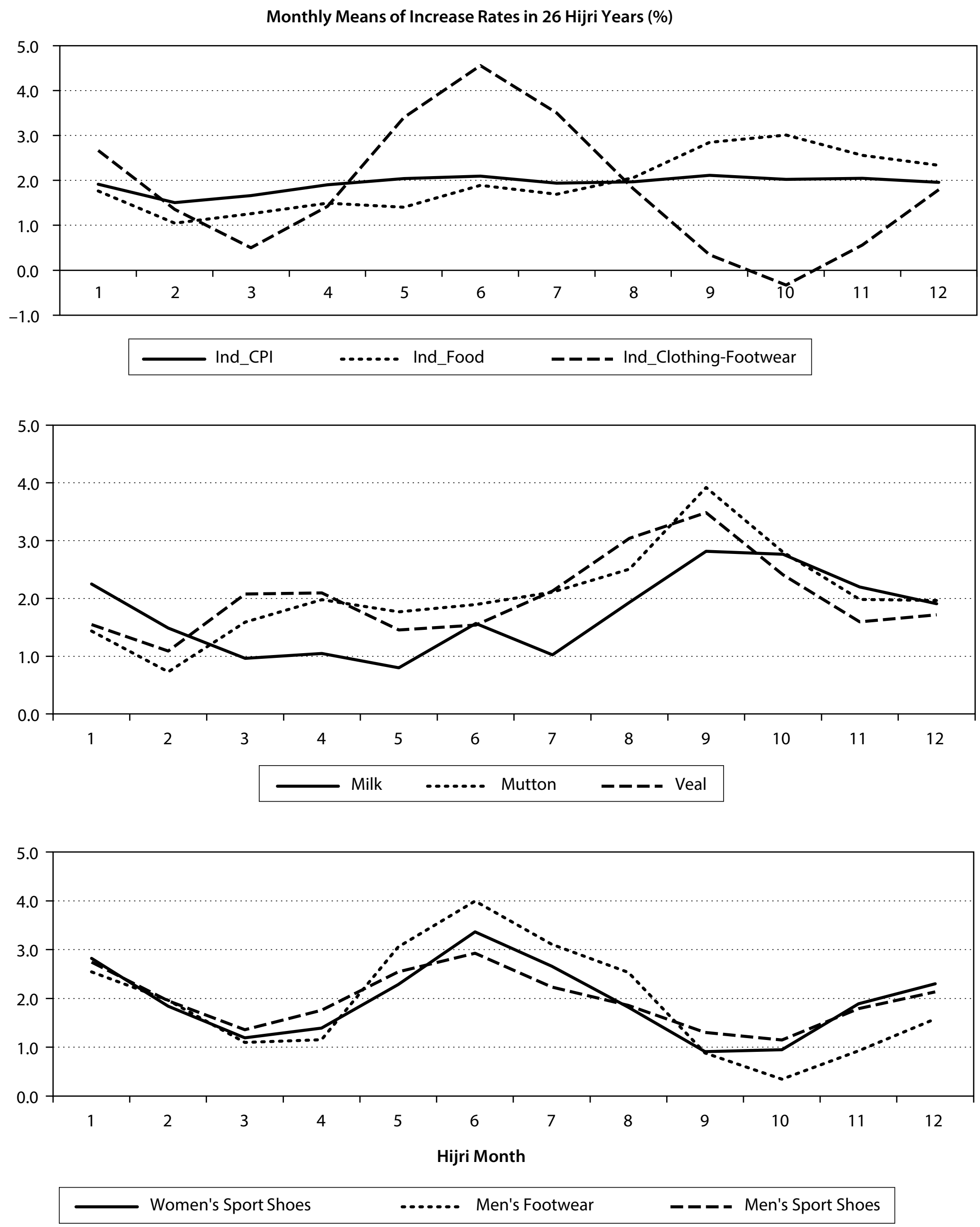
8 – Shaban		9 – Ramadan		10 – Shawwal	
Indicator	**Rank***	**Indicator**	**Rank***	**Indicator**	**Rank***
Bread	12	Ind_CPI	12	Ind_Food	12
Corn Oil	12	Butter	12	Kasar Cheese	12
Dessert	12	Milk	12	Olive	12
Egg	12	Mutton	12	Onion	12
Lentils	12	Veal	12	Tomato	12
Olive Oil	12	Ind_Food	11	Butter	11
Sun-Flower Oil	12	Airplane Fare	11	Garlic-Flavored Sausage	11
Wheat Flour	12	Carbonated Fruity Beverages	11	Milk	11
Bus Fare (Intra-Urban)	11	Dessert	11	Mutton	11
Dry Bean	11	Olive Oil	11	Tea	11
Olive	11	Raki	11	Dry Bean	2
Veal	11	Tomato	11	Egg	2
Airplane Fare	2	Wine	11	Lentils	2
Potato	1	Ind_Clothing-Footwear	2	Sun-Flower Oil	2
		Men's Footwear	2	Women's Sport Shoes	2
		Men's Sport Shoes	2	Ind_Clothing-Footwear	1
		Chickpea	1	Bread	1
		Women's Sport Shoes	1	Fruit Juice	1
				Men's Footwear	1
				Men's Sport Shoes	1
				Women's Footwear	1

Note: * 1: lowest increase rate, 12: highest increase rate.
Source: Authors' calculation

The price movements related to Ramadan may affect the previous and next months. The demand for some items may increase in the previous month due to preparation for Ramadan. On the other hand, the price of some items, stocked for Ramadan and Eid al-Fitr (the religious holiday just after the month Ramadan) but could not be sold, may decrease in the next month, and the increased price at the end of Ramadan may be misreported and shifted to the next month. Besides, the calendar transformation mechanism, namely the assumption of the stability of prices during each Gregorian month, may carry some of the price movement to and from the previous and next month of Ramadan. Therefore, the price movements in the previous and next months of Ramadan may provide additional information about the *Ramadan effect*.

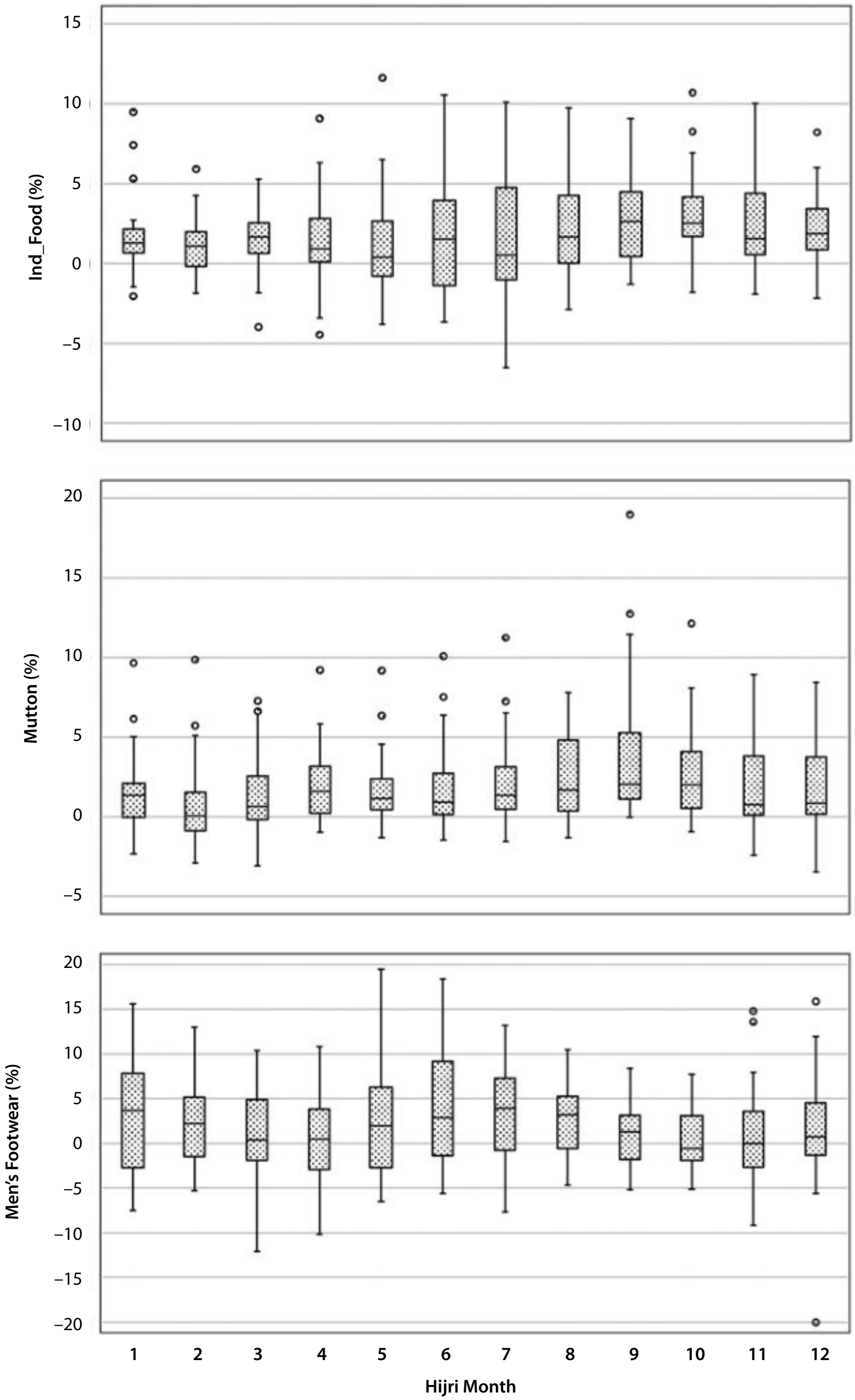
In the 8th month Shaban, the increase rates of eight items' prices are the highest, and four items' rates are the second-highest (Table 3). However, only one item's with the highest (*Egg*), and one item's with the second-highest (*Veal*) increase rates have significantly different means (see Table A5 in the Annex). The difference of the means of seven items with highest (*Bread, Corn Oil, Dessert, Lentils, Olive Oil,* *Sun-Flower Oil, Wheat Flour*) and three items with the second-highest (*Bus Fare (Intra-Urban), Dry Bean, Olive*) increase rate in Shaban are not significant. There is not any item with the average increase rate in the 8th month that is significantly lower than in other months.

Figure 1 Monthly means of increase rates of selected prices in 26 Hijri years



Source: Authors' construction

Figure 2 Monthly distributions of increase rates of selected prices in 26 Hijri years



Source: Authors' construction

In Shawwal, the 10th month, the *Food Price Index,* and prices of four items increased most, and the increase rates of prices of the other five items are the second-highest (Table 3). The *Food Price Index* and the price of *Tomato* increased significantly more (see Table A6 in the Annex). Other items with the highest increase rates in Shawwal (*Kasar Cheese, Olive, Onion*) did not increase significantly higher than in other months. Although it has the second-highest increase rate in Shawwal, the rate of *Milk* is significantly higher than in other months. The differences in the increase rates of four items (*Butter, Garlic-Flavored Sausage, Mutton, Tea*) in this month from other months are not significant. *The Clothing and Footwear Price Index* and the prices of two of five items with lowest (*Men's Footwear, Men's Sport Shoes*) and one of the five items with second lowest (*Women's Sport Shoes*) increase rate in Shawwal increased significantly lower than in other months.

Finally, the combined price movements in the 8th, 9th, and 10th Hijri months (Shaban, Ramadan, Shawwal) are evaluated by testing the significance of the differences between the means of monthly increase rates of three months and the means of the rates of other nine months for all indices and items. The items with significantly different means of the increase rates and the test parameters are listed in Table A7 in the Annex.

Although the increase rate of *CPI* is the highest on average in Ramadan, the mean of the increase rates of CPI in Ramadan is not significantly higher than the mean of other months. However, the mean of the increase rates of *Food Price Index*, a sub-index of CPI is highest in Shawwal and second highest in Ramadan. The difference of the mean of the rates in Shawwal from other months is significant (*sig.: 0.029*), but it is not in Ramadan. On the other hand, the increase rate of another sub-index, *Clothing and Footwear Price Index*, is significantly lower than other months both in Shawwal (*sig: 0.002*) and Ramadan (*sig.: 0.018*). However, the comparison of the mean of increase rates of combined three months with the mean of the remaining nine months presents more significant differences (Table 4). The monthly increase rates of the *Food Price Index* and prices of *Bus Fare, Milk, Mutton*, and *Veal* are significantly (at %1 sig. level) higher in the three months than their increase rates in other months.

Table 4 The index and items with monthly increase rates significantly higher and lower than other months and the significance levels

Indicator	Sig. (1-tailed)			
	Ramadan	Shaban	Shawwal	3 Months
Higher than Other Months				
Ind_Food			0.029**	0.009***
Bus Fare (Intra-Urban)				0.006***
Egg		0.018**		
Milk	0.030**		0.037**	0.005***
Mutton	0.017**			0.001***
Tomato			0.046**	0.019**
Veal	0.004***	0.033**		0.000***
Lower than Other Months				
Ind_Clothing-Footwear	0.018**		0.002***	0.004***
Men's Footwear			0.012**	
Men's Sport Shoes			0.036**	0.043**
Men's Trousers				0.040**
Skirt				0.029**
Women's Sport Shoes			0.024**	0.012**

Note: *** and ** implies that the difference is significant at 1% and 5% level, respectively.
Source: Authors' calculation

3.2 Production in Ramadan

Similar methodology used in testing the prices is applied to one digit sub-indices of the IPI. The means of monthly increase rates in 34 Hijri years (1407–1440) are listed and ranked (see Table A8 in the Annex). The production indices of two-digit or more specific activities comprised within IPI are worth to test. However, for the production indices of sub-activities, the calendar adjusted Industrial Production Index is available since 2005, and it corresponds to 15 Hijri years. Since the data is considered not enough for such an analysis, the sub-sectors are excluded.

As it is presented in Table A8 in the Annex, the production indices of *B-Mining and quarrying* and C- *Manufacturing* increased least in Ramadan, actually decreased on average. The increase rates of two indices in Ramadan (Mth_9 in Table 5) are tested against the null hypotheses that the level of difference, more specifically the decreased rate in Ramadan compared to other months, is not significant (Table 5).

Table 5 T-test results of increase rates of production indices (Ramadan-others)

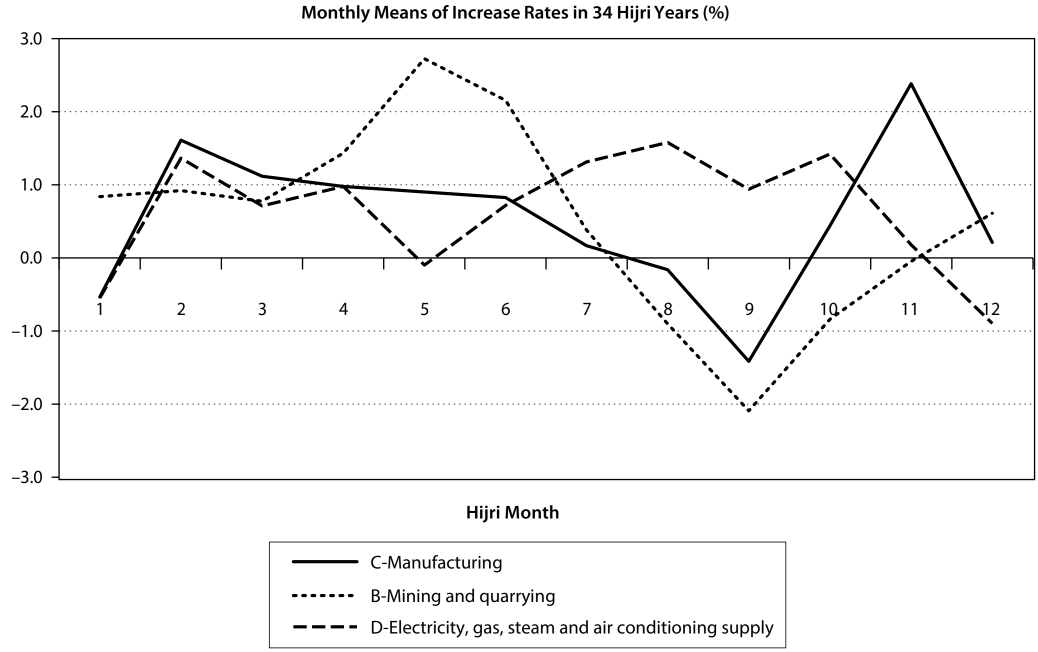
Ramadan and others		N	Mean	Std. Error Mean
B-Mining and quarrying	Mth_9	34	–2.091	0.984
	Others	374	0.732	0.404
C-Manufacturing	Mth_9	34	–1.417	0.902
	Others	374	0.720	0.330
D-Electricity, gas, steam and air conditioning supply	Mth_9	34	0.941	1.041
	Others	374	0.611	0.253

Indicator	Equal Variances Assumed?	Levene's Test for Equality of Variances		t-test for Equality of Means Ramadan and others						
		F	Sig.	t	df	Sig. (1-tailed)	Mean Diffe-rence	Std. Error Diffe-rence	95% Confidence Interval of the Difference	
									Lower	Upper
B-Mining and quarrying	Yes	2.716	0.1001	–2.056	406	0.020**	–2.823	1.373	–5.523	–0.123
	No			–2.653	44.943	0.005	–2.823	1.064	–4.966	–0.680
C-Manufacturing	Yes	1.763	0.185	–1.894	406	0.029**	–2.138	1.129	–4.357	0.081
	No			–2.225	42.363	0.016	–2.138	0.961	–4.076	–0.199
D-Electricity, gas, steam and air conditioning supply	Yes	2.869	0.091	0.369	406	0.356	0.330	0.895	–1.430	2.090
	No			0.308	37.001	0.380	0.330	1.071	–1.841	2.501

Note: *** and ** implies that the difference is significant at 1% and 5% level, respectively.
Source: Authors' calculation

The increase rates of both tested indicators are significantly less than the rates of other months on average (*sig.: 0.020* for *B-Mining and quarrying* and *sig.: 0.029* for *C-Manufacturing*). On the other hand, the mean of the increase rates of the *D-Electricity, gas, steam and air conditioning supply index* in Ramadan is over the average of other months. Still, it is neither the highest increase rate among the months nor not significantly higher than the means in other months (Figure 3). The analysis indicates that manufacturing production and mining activities decrease significantly in Ramadan.

Figure 3 Monthly means of increase rates of production in 34 Hijri years



Source: Authors' construction

CONCLUSION

CPI of Turkey is found to have the highest increase rate, on average, in Ramadan, among the Hijri months, but the difference between the means of its increase rates in Ramadan and other months is not significant. However, the means of the increase rates of the prices of three food items (*Milk, Mutton, and Veal*) in Ramadan are significantly higher than the means of other months. On the other hand, the increase rate of *Clothing and Footwear Price Index* in Ramadan is significantly lower than in other months.

In Shaban and Shawwal, the previous and next months of Ramadan, respectively, the means of the increase rates of the prices of several items are significantly high, which may be related to the Ramadan effect. More importantly, the mean of the monthly increase rates in the combined three months (Shaban, Ramadan, and Shawwal) is significantly higher than in the remaining nine months for more items than it is in individual months. Besides, the significance levels are mostly better, implying that the Ramadan effect is expanded to three months. However, it must be noted that the expansion may be partly false for two reasons. At first, the price movements of some items that emerge at the end of the months may be misreported and technically shifted to next month due to the methodology used. Secondly, the assumption of the stability of prices during each Gregorian month, which is essential for calendar transformation of the indicators, may carry some part of the price movement to and from the previous and next month of Ramadan.

The existence of the Ramadan effect on industrial production in Turkey is also observed. Two of the three sub-indices of Industrial Production Index (*B-Mining and quarrying* and *C-Manufacturing*) are decreased in Ramadan significantly more than in other months.

Utilizing the findings may improve the quality of economic forecasts, such as the accuracy of inflation forecasting models. Besides, the impact on production should be considered in the calculation of adjusted indices with other seasonal effects.

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ANNEX: Supplementary tables and figures

Table A1 The sub-items of 1994 = 100 CPI that used in linking the prices

Item – 2003 = 100 CPI	Item – 1994 = 100 CPI
Rice	Rice (Baldo)
Bread	White bread
Dessert	Desserts (Baklava)
Veal	Veal (inced meat)
Mutton	Mutton (Meat cut in large pieces)
Poultry	Poultry (Whole)
White Cheese	White cheese (Semi-skimmed)
Kasar Cheese	Kosher cheese (Fresh)
Lentils	Lentils (Red)
Olive	Olive (Black)
Granulated Sugar	Powdered sugar
Cube Sugar	Lump sugar
Tea	Tea (Produced by Private Sector)
Carbonated Fruity Beverages	Carbonated fruity beverages (Plastic bottle)
Coke	Coke (Plastic bottle)
Fruit Juice	Fruit Juices (Carton box 1lt.)
Raki	Raki (average of 35 cl and 70 cl)
Wine	Wine (Produced by Private Sector)
Beer	Beer (Produced by Private Sector)
Men's Trousers	Trousers (Terrycloth Men)
Skirt	Skirts (Linen Women)
Women's Trousers	Trousers (Gabardin Women)
Men's Footwear	Men's footwear (Without lace)
Men's Sport Shoes	Sport shoes (Leather Men)
Women's Footwear	Women's footwear (Without lace)
Women's Sport Shoes	Sport shoes (Leather Women)
Bus Fare (Intra-Urban)	Bus fare (Adana)
Airplane Fare	Airplane fare (İzmir)

Source: TURKSTAT

Table A2 The Hijri New Year and the corresponding Gregorian date

Hijri New Year	Corresponding Gregorian Date
1.1.1407	5.9.1986
1.1.1408	26.8.1987
1.1.1409	14.8.1988
1.1.1410	3.8.1989
1.1.1411	23.7.1990
1.1.1412	13.7.1991
1.1.1413	2.7.1992
1.1.1414	21.6.1993
1.1.1415	11.06.1994
1.1.1416	31.05.1995
1.1.1417	19.05.1996
1.1.1418	8.5.1997
1.1.1419	27.4.1998
1.1.1420	17.4.1999
1.1.1421	6.4.2000
1.1.1422	26.3.2001
1.1.1423	15.3.2002
1.1.1424	4.3.2003
1.1.1425	21.2.2004
1.1.1426	10.2.2005
1.1.1427	31.1.2006
1.1.1428	20.1.2007
1.1.1429	10.1.2008
1.1.1430	29.12.2008
1.1.1431	17.12.2009
1.1.1432	7.12.2010
1.1.1433	26.11.2011
1.1.1434	15.11.2012
1.1.1435	4.11.2013
1.1.1436	25.10.2014
1.1.1437	14.10.2015
1.1.1438	2.10.2016
1.1.1439	21.9.2017
1.1.1440	11.9.2018

Source: Presidency of Religious Affairs of Turkey

Table A3 Monthly means of increase rates of prices in 26 Hijri years and their ranks among months

Indicator	Monthly Means of Increase Rates in 26 Hijri Years (%)												Rank of the Month (1:lowest, 12:highest)											
	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12
1 Ind_CPI	1.91	1.50	1.66	1.90	2.04	2.10	1.94	1.97	2.11	2.02	2.05	1.96	4	1	2	3	9	11	5	7	12	8	10	6
2 Ind_Food	1.76	1.05	1.26	1.49	1.40	1.89	1.69	2.06	2.85	3.01	2.56	2.33	6	1	2	4	3	7	5	8	11	12	10	9
3 Ind_Clothing-Footwear	2.67	1.35	0.50	1.42	3.40	4.56	3.50	1.82	0.34	–0.33	0.56	1.79	9	5	3	6	10	12	11	8	2	1	4	7
4 Airplane Fare	0.30	2.61	3.13	3.78	3.21	1.29	2.30	1.23	3.60	2.94	1.75	2.37	1	7	9	12	10	3	5	2	11	8	4	6
5 Beer	2.42	2.39	3.01	2.64	1.85	1.39	0.96	1.50	2.30	2.42	3.21	2.68	8	6	11	9	4	2	1	3	5	7	12	10
6 Bread	2.01	2.43	1.82	2.32	1.48	1.75	2.73	2.77	2.04	1.11	1.53	1.33	7	10	6	9	3	5	11	12	8	1	4	2
7 Bus Fare (Intra-Urban)	0.71	0.46	1.22	1.76	2.11	2.13	2.19	2.94	2.94	2.72	1.47	3.46	2	1	3	5	6	7	8	11	10	9	4	12
8 Butter	2.11	1.81	1.40	1.51	1.62	2.54	1.68	1.66	2.73	2.59	2.19	1.80	8	7	1	2	3	10	5	4	12	11	9	6
9 Carbonated Fruity Beverages	1.85	1.41	1.43	1.08	1.10	1.85	1.63	1.79	2.04	1.58	1.81	2.47	9	3	4	1	2	10	6	7	11	5	8	12
10 Chickpea	1.79	2.52	2.45	1.71	1.57	2.21	2.39	2.34	1.24	1.77	1.96	1.78	6	12	11	3	2	8	10	9	1	4	7	5
11 Coke	1.91	1.34	1.29	0.76	1.09	1.98	1.92	1.77	2.00	1.54	2.06	2.60	7	4	3	1	2	9	8	6	10	5	11	12
12 Corn Oil	1.72	2.19	1.69	1.76	1.89	1.97	2.14	2.54	1.45	1.24	0.74	1.09	6	11	5	7	8	9	10	12	4	3	1	2
13 Cube Sugar	1.48	1.85	1.65	2.04	2.30	1.99	2.03	1.79	1.86	1.74	1.82	1.42	2	7	3	11	12	9	10	5	8	4	6	1
14 Dessert	2.19	1.72	1.80	2.10	2.23	1.93	2.22	2.71	2.26	1.86	1.69	1.45	8	3	4	7	10	6	9	12	11	5	2	1
15 Dry Bean	1.99	2.88	2.16	1.84	1.28	1.94	2.74	2.84	1.55	1.24	1.44	1.20	8	12	9	6	3	7	10	11	5	2	4	1
16 Egg	–3.47	1.61	4.93	1.79	1.06	3.28	1.85	5.69	1.78	0.29	5.34	2.39	1	4	10	6	3	9	7	12	5	2	11	8
17 Fruit Juice	2.00	2.32	1.70	1.60	1.39	1.82	1.58	1.67	1.45	1.36	1.72	2.21	10	12	7	5	2	9	4	6	3	1	8	11
18 Garlic-Flavored Sausage	1.83	1.68	1.97	2.71	1.75	1.76	1.71	1.90	1.78	2.17	1.68	1.61	8	2	10	12	5	6	4	9	7	11	3	1

Table A3 continuation

Indicator	Monthly Means of Increase Rates in 26 Hijri Years (%)												Rank of the Month (1:lowest, 12:highest)											
	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12
19 Granulated Sugar	1.45	2.24	1.54	2.19	2.58	1.90	1.91	1.81	2.14	1.68	1.66	1.42	2	11	3	10	12	7	8	6	9	5	4	1
20 Kasar Cheese	2.27	1.66	1.35	1.51	1.89	2.24	1.86	1.71	1.69	2.38	2.15	2.19	11	3	1	2	7	10	6	5	4	12	8	9
21 Lentils	1.69	1.46	2.17	2.09	2.03	1.92	2.96	2.96	1.95	1.46	1.58	1.31	5	3	10	9	8	6	11	12	7	2	4	1
22 Men's Footwear	2.54	1.97	1.10	1.16	3.05	4.00	3.11	2.53	0.88	0.35	0.92	1.58	9	7	4	5	10	12	11	8	2	1	3	6
23 Men's Sport Shoes	2.74	1.95	1.36	1.76	2.54	2.93	2.24	1.86	1.30	1.15	1.79	2.13	11	7	3	4	10	12	9	6	2	1	5	8
24 Men's Trousers	5.26	3.00	0.05	−0.52	0.33	1.68	1.06	1.18	0.75	0.78	2.92	4.85	12	10	2	1	3	8	6	7	4	5	9	11
25 Milk	2.25	1.49	0.96	1.05	0.80	1.56	1.02	1.93	2.82	2.76	2.20	1.91	10	5	2	4	1	6	3	8	12	11	9	7
26 Mutton	1.43	0.73	1.59	1.98	1.77	1.90	2.11	2.51	3.92	2.80	1.98	1.97	2	1	3	7	4	5	9	10	12	11	8	6
27 Olive	1.88	1.76	1.79	1.77	1.76	1.96	1.75	2.02	1.96	2.11	1.68	1.66	8	5	7	6	4	9	3	11	10	12	2	1
28 Olive Oil	1.53	1.75	2.39	2.41	1.49	1.96	1.99	2.65	2.48	2.04	1.55	1.28	3	5	9	10	2	6	7	12	11	8	4	1
29 Onion	5.32	5.62	4.37	3.00	−0.58	−2.84	−1.83	1.05	4.70	6.15	1.63	2.49	10	11	8	7	3	1	2	4	9	12	5	6
30 Potato	6.53	5.12	4.24	5.55	2.13	0.00	1.35	−0.07	1.99	1.45	0.13	2.91	12	10	9	11	7	2	4	1	6	5	3	8
31 Poultry	1.11	5.84	7.23	4.63	1.49	0.53	0.82	1.55	4.16	0.66	−2.57	−1.73	6	11	12	10	7	3	5	8	9	4	1	2
32 Raki	2.81	1.65	3.63	2.82	2.73	1.62	1.38	2.91	3.19	2.00	2.56	2.07	8	3	12	9	7	2	1	10	11	4	6	5
33 Rice	2.06	2.71	2.79	2.74	1.59	2.14	1.73	1.73	1.39	1.04	1.04	0.99	8	10	12	11	5	9	7	6	4	3	2	1
34 Skirt	5.05	2.29	0.01	−0.54	0.42	2.26	1.80	0.45	0.11	1.10	4.27	5.11	11	9	2	1	4	8	7	5	3	6	10	12
35 Sun–Flower Oil	2.01	2.25	1.88	1.97	1.76	1.61	2.02	2.39	1.88	1.19	0.85	1.33	9	11	7	8	5	4	10	12	6	2	1	3
36 Tea	2.33	2.22	2.90	1.70	1.29	1.36	1.96	1.50	1.63	2.77	1.65	1.66	10	9	12	7	1	2	8	3	4	11	5	6
37 Tomato	4.96	−3.65	−4.86	−2.66	−1.66	4.64	8.80	2.74	10.95	13.53	8.88	10.22	7	2	1	3	4	6	8	5	11	12	9	10
38 Veal	1.55	1.09	2.07	2.09	1.45	1.54	2.13	3.04	3.49	2.41	1.59	1.72	4	1	7	8	2	3	9	11	12	10	5	6
39 Wheat Flour	1.70	2.10	2.04	1.41	0.91	1.64	2.54	2.61	1.80	1.66	1.65	1.49	7	10	9	2	1	4	11	12	8	6	5	3
40 Whisky	2.67	1.47	3.36	2.41	2.74	1.55	1.52	2.06	2.69	2.53	2.60	2.76	8	1	12	5	10	3	2	4	9	6	7	11
41 White Cheese	2.51	1.55	1.33	1.31	1.84	2.52	2.17	2.01	1.77	1.96	1.83	3.67	10	3	2	1	6	11	9	8	4	7	5	12
42 Wine	1.90	1.92	2.90	2.19	1.74	2.07	1.86	2.29	2.33	2.27	2.17	1.66	4	5	12	8	2	6	3	10	11	9	7	1
43 Women's Footwear	2.37	0.95	0.65	0.86	3.31	4.59	3.17	2.04	1.10	0.50	1.36	1.88	9	4	2	3	11	12	10	8	5	1	6	7
44 Women's Sport Shoes	2.82	1.84	1.19	1.39	2.29	3.36	2.66	1.82	0.91	0.95	1.89	2.30	11	6	3	4	8	12	10	5	1	2	7	9
45 Women's Trousers	2.67	1.32	−0.12	0.23	2.85	5.74	4.38	2.92	0.55	−0.54	0.72	1.79	8	6	2	3	9	12	11	10	4	1	5	7
46 Yoghurt	2.43	1.73	1.20	1.59	1.80	2.25	1.39	1.43	2.13	2.00	1.87	2.02	12	5	1	4	6	11	2	3	10	8	7	9

Source: Authors' calculation

Table A4 T-test results of means of increase rates of prices, Ramadan-others
A. Group statistics

Ramadan and others		N	Mean	Std. Deviation	Std Error Mean.
Ind_CPI	Mth_9	26	2.113	2.106	0.413
	Others	286	1.914	2.007	0.119
Ind_Food	Mth_9	26	2.847	2.984	0.585
	Others	286	1.865	2.987	0.177
Ind_Clothing-Footwear	Mth_9	26	0.344	3.327	0.652
	Others	286	1.931	5.679	0.336
Dessert	Mth_9	26	2.260	1.978	0.388
	Others	286	1.991	2.000	0.118
Veal	Mth_9	26	3.487	3.222	0.632
	Others	286	1.880	2.924	0.173
Mutton	Mth_9	26	3.918	4.553	0.893
	Others	286	1.887	2.811	0.166
Milk	Mth_9	26	2.818	2.880	0.565
	Others	286	1.631	3.081	0.182
Butter	Mth_9	26	2.731	2.918	0.572
	Others	286	1.900	2.784	0.165
Olive Oil	Mth_9	26	2.481	4.412	0.865
	Others	286	1.914	3.728	0.220
Tomato	Mth_9	26	10.946	23.978	4.703
	Others	286	3.721	23.262	1.376
Chickpea	Mth_9	26	1.237	3.483	0.683
	Others	286	2.045	3.584	0.212
Carbonated Fruity Beverages	Mth_9	26	2.044	2.456	0.482
	Others	286	1.635	3.050	0.180
Raki	Mth_9	26	3.195	6.658	1.306
	Others	286	2.380	4.560	0.270
Wine	Mth_9	26	2.326	3.202	0.628
	Others	286	2.088	3.135	0.185
Men's Footwear	Mth_9	26	0.881	3.607	0.707
	Others	286	2.028	5.686	0.336
Men's Sport Shoes	Mth_9	26	1.301	2.993	0.587
	Others	286	2.041	3.995	0.236
Women's Sport Shoes	Mth_9	26	0.907	2.900	0.569
	Others	286	2.047	4.126	0.244
Airplane Fare	Mth_9	26	3.597	9.029	1.771
	Others	286	2.265	6.655	0.394

Source: Authors' calculation

Table A4 T-test results of means of increase rates of prices, Ramadan-others (cont'd)
B. T-test parameters

Indicator	Equal Variances Assumed?	Levene's Test for Equal. of Varian.		t-test for Equality of Means Ramadan and others						
		F	Sig.	t	df	Sig. (1-tailed)	Mean Diffe-rence	Std. Error Diffe-rence	95% Confidence Interval of the Difference	
									Lower	Upper
Ind_CPI	Yes	0.220	0.639	0.483	310	0.315	0.199	0.413	−0.613	1.012
	No			0.464	29.281	0.323	0.199	0.430	−0.679	1.078
Ind_Food	Yes	0.070	0.791	1.605	310	0.055	0.982	0.612	−0.222	2.186
	No			1.606	29.740	0.059	0.982	0.611	−0.267	2.231
Ind_ Clothing-Footwear	Yes	12.751	0.000***	−1.403	310	0.081	−1.588	1.132	−3.815	0.640
	No			−2.164	39.751	0.018**	−1.588	0.734	−3.071	−0.104
Dessert	Yes	0.177	0.674	0.656	310	0.256	0.268	0.409	−0.537	1.074
	No			0.662	29.841	0.257	0.268	0.406	−0.560	1.097
Veal	Yes	0.215	0.643	2.659	310	0.004***	1.606	0.604	0.418	2.795
	No			2.452	28.869	0.010	1.606	0.655	0.266	2.947
Mutton	Yes	8.189	0.005***	3.316	310	0.001	2.030	0.612	0.826	3.235
	No			2.236	26.760	0.017**	2.030	0.908	0.166	3.895
Milk	Yes	0.158	0.692	1.891	310	0.030**	1.187	0.628	−0.048	2.422
	No			2.000	30.442	0.027	1.187	0.594	−0.024	2.398
Butter	Yes	1.072	0.301	1.451	310	0.074	0.831	0.573	−0.296	1.957
	No			1.395	29.290	0.087	0.831	0.596	−0.387	2.048
Olive Oil	Yes	1.859	0.174	0.731	310	0.233	0.567	0.776	−0.960	2.094
	No			0.635	28.342	0.265	0.567	0.893	−1.261	2.395
Tomato	Yes	0.002	0.969	1.512	310	0.066	7.224	4.777	−2.175	16.624
	No			1.474	29.442	0.075	7.224	4.900	−2.790	17.238
Chickpea	Yes	0.692	0.406	−1.102	310	0.136	−0.808	0.733	−2.249	0.634
	No			−1.129	30.020	0.134	−0.808	0.715	−2.268	0.653
Carbonated Fruity Beverages	Yes	0.014	0.906	0.664	310	0.254	0.409	0.616	−0.803	1.621
	No			0.795	32.447	0.216	0.409	0.514	−0.638	1.456
Raki	Yes	2.868	0.091	0.834	310	0.202	0.814	0.976	−1.106	2.734
	No			0.611	27.173	0.273	0.814	1.333	−1.921	3.549
Wine	Yes	0.765	0.383	0.370	310	0.356	0.238	0.643	−1.028	1.503
	No			0.363	29.526	0.360	0.238	0.655	−1.100	1.576
Men's Footwear	Yes	6.235	0.013**	−1.009	310	0.157	−1.147	1.136	−3.383	1.089
	No			−1.464	37.407	0.076	−1.147	0.783	−2.733	0.439
Men's Sport Shoes	Yes	1.658	0.199	−0.921	310	0.179	−0.740	0.804	−2.322	0.841
	No			−1.170	33.673	0.125	−0.740	0.633	−2.027	0.546
Women's Sport Shoes	Yes	1.776	0.184	−1.377	310	0.085	−1.140	0.828	−2.769	0.489
	No			−1.842	34.942	0.037	−1.140	0.619	−2.396	0.117
Airplane Fare	Yes	3.076	0.080	0.946	310	0.173	1.332	1.409	−1.440	4.104
	No			0.734	27.525	0.234	1.332	1.814	−2.386	5.050

Note: *** and ** implies that the difference is significant at 1% and 5% level, respectively.
Source: Authors' calculation

Table A5 T-test results of means of increase rates of prices, Shaban-others
A. Group statistics

Shaban and others		N	Mean	Std. Deviation	Std Error Mean.
Wheat Flour	Mth_8	26	2.614	4.147	0.813
	Others	286	1.722	2.585	0.153
Bread	Mth_8	26	2.770	4.085	0.801
	Others	286	1.869	2.676	0.158
Dessert	Mth_8	26	2.713	2.439	0.478
	Others	286	1.950	1.944	0.115
Veal	Mth_8	26	3.041	2.226	0.437
	Others	286	1.921	3.023	0.179
Egg	Mth_8	26	5.686	9.774	1.917
	Others	286	1.896	8.730	0.516
Olive Oil	Mth_8	26	2.652	5.063	0.993
	Others	286	1.898	3.652	0.216
Sun-Flower Oil	Mth_8	26	2.392	6.563	1.287
	Others	286	1.705	3.394	0.201
Corn Oil	Mth_8	26	2.540	6.617	1.298
	Others	286	1.625	3.358	0.199
Potato	Mth_8	26	−0.066	9.770	1.916
	Others	286	2.855	13.255	0.784
Dry Bean	Mth_8	26	2.845	5.679	1.114
	Others	286	1.843	3.570	0.211
Lentils	Mth_8	26	2.965	4.582	0.899
	Others	286	1.875	4.409	0.261
Olive	Mth_8	26	2.024	2.450	0.480
	Others	286	1.826	1.786	0.106
Bus Fare (Intra-Urban)	Mth_8	26	2.942	4.914	0.964
	Others	286	1.925	3.292	0.195
Airplane Fare	Mth_8	26	1.229	3.039	0.596
	Others	286	2.480	7.117	0.421

Source: Authors' calculation

Table A5 T-test results of means of increase rates of prices, Shaban-others (cont'd)
B. T-test parameters

Indicator	Equal Variances Assumed?	Levene's Test for Equal. of Varian. F	Levene's Test for Equal. of Varian. Sig.	t-test for Equality of Means Shaban and others: t	df	Sig. (1-tailed)	Mean Diffe-rence	Std. Error Diffe-rence	95% Confidence Interval of the Difference: Lower	Upper
Wheat Flour	Yes	6.861	0.009***	1.586	310	0.057	0.892	0.562	–0.214	1.998
	No			1.077	26.794	0.145	0.892	0.828	–0.807	2.590
Bread	Yes	5.901	0.016**	1.562	310	0.060	0.901	0.577	–0.234	2.036
	No			1.103	26.985	0.140	0.901	0.817	–0.775	2.576
Dessert	Yes	5.398	0.021**	1.874	310	0.031	0.763	0.407	–0.038	1.565
	No			1.552	27.963	0.066	0.763	0.492	–0.244	1.771
Veal	Yes	1.469	0.226	1.843	310	0.033**	1.120	0.608	–0.076	2.316
	No			2.374	34.001	0.012	1.120	0.472	0.161	2.079
Egg	Yes	0.562	0.454	2.098	310	0.018**	3.790	1.806	0.236	7.344
	No			1.909	28.745	0.033	3.790	1.985	–0.271	7.852
Olive Oil	Yes	1.934	0.165	0.972	310	0.166	0.754	0.775	–0.772	2.279
	No			0.742	27.416	0.232	0.754	1.016	–1.330	2.837
Sun-Flower Oil	Yes	4.050	0.045**	0.895	310	0.186	0.688	0.768	–0.824	2.199
	No			0.528	26.229	0.301	0.688	1.303	–1.989	3.364
Corn Oil	Yes	3.162	0.076	1.198	310	0.116	0.915	0.764	–0.588	2.417
	No			0.697	26.183	0.246	0.915	1.313	–1.783	3.612
Potato	Yes	0.456	0.500	–1.096	310	0.137	–2.921	2.665	–8.164	2.322
	No			–1.411	33.984	0.084	–2.921	2.070	–7.128	1.287
Dry Bean	Yes	9.599	0.002***	1.293	310	0.098	1.002	0.775	–0.523	2.527
	No			0.884	26.826	0.192	1.002	1.134	–1.324	3.329
Lentils	Yes	1.678	0.196	1.203	310	0.115	1.090	0.906	–0.693	2.873
	No			1.165	29.368	0.127	1.090	0.936	–0.823	3.003
Olive	Yes	6.058	0.014**	0.523	310	0.301	0.198	0.379	–0.547	0.943
	No			0.403	27.469	0.345	0.198	0.492	–0.810	1.207
Bus Fare (Intra-Urban)	Yes	2.061	0.152	1.439	310	0.076	1.017	0.707	–0.373	2.408
	No			1.035	27.077	0.155	1.017	0.983	–1.000	3.034
Airplane Fare	Yes	2.081	0.150	–0.888	310	0.188	–1.251	1.409	–4.024	1.521
	No			–1.715	54.939	0.046	–1.251	0.730	–2.714	0.211

Note: *** and ** implies that the difference is significant at 1% and 5% level, respectively.
Source: Authors' calculation

Table A6 T-test results of means of increase rates of prices, Shawwal-others
A. Group statistics

Shawwal and others		N	Mean	Std. Deviation	Std Error Mean.
Ind_Food	Mth_10	26	3.013	2.794	0.548
	Others	286	1.850	2.997	0.177
Ind_Clothing-Footwear	Mth_10	26	–0.329	3.501	0.687
	Others	286	1.993	5.648	0.334
Bread	Mth_10	26	1.114	1.483	0.291
	Others	286	2.020	2.904	0.172
Mutton	Mth_10	26	2.800	3.117	0.611
	Others	286	1.989	3.026	0.179
Garlic-Flavored Sausage	Mth_10	26	2.170	1.487	0.292
	Others	286	1.853	2.671	0.158
Milk	Mth_10	26	2.763	2.180	0.427
	Others	286	1.636	3.133	0.185
Kasar Cheese	Mth_10	26	2.382	1.475	0.289
	Others	286	1.864	3.204	0.189
Egg	Mth_10	26	0.287	9.011	1.767
	Others	286	2.387	8.849	0.523
Butter	Mth_10	26	2.586	2.240	0.439
	Others	286	1.913	2.842	0.168
Sun-Flower Oil	Mth_10	26	1.190	2.687	0.527
	Others	286	1.814	3.830	0.226
Tomato	Mth_10	26	13.532	28.599	5.609
	Others	286	3.486	22.710	1.343
Onion	Mth_10	26	6.153	10.139	1.988
	Others	286	2.085	13.586	0.803
Dry Bean	Mth_10	26	1.236	3.285	0.644
	Others	286	1.989	3.830	0.226
Lentils	Mth_10	26	1.460	3.027	0.594
	Others	286	2.012	4.534	0.268
Olive	Mth_10	26	2.112	1.723	0.338
	Others	286	1.818	1.858	0.110
Tea	Mth_10	26	2.769	4.666	0.915
	Others	286	1.837	3.659	0.216
Fruit Juice	Mth_10	26	1.355	1.439	0.282
	Others	286	1.771	2.484	0.147
Men's Footwear	Mth_10	26	0.345	3.332	0.653
	Others	286	2.076	5.689	0.336
Men's Sport Shoes	Mth_10	26	1.149	2.179	0.427
	Others	286	2.055	4.038	0.239
Women's Footwear	Mth_10	26	0.499	5.355	1.050
	Others	286	2.025	6.559	0.388
Women's Sport Shoes	Mth_10	26	0.949	2.440	0.478
	Others	286	2.043	4.153	0.246

Source: Authors' calculation

Table A6 T-test results of means of increase rates of prices, Shawwal-others (cont'd)
B. T-test parameters

Indicator	Equal Variances Assumed?	Levene's Test for Equal. of Varian.		t-test for Equality of Means Shawwal and others						
		F	Sig.	t	df	Sig. (1-tailed)	Mean Diffe-rence	Std. Error Diffe-rence	95% Confidence Interval of the Difference	
									Lower	Upper
Ind_Food	Yes	0.293	0.588	1.904	310	0.029**	1.163	0.611	–0.039	2.365
	No			2.019	30.474	0.026	1.163	0.576	–0.012	2.339
Ind_ Clothing-Footwear	Yes	11.267	0.001***	–2.058	310	0.020	–2.321	1.128	–4.540	–0.102
	No			–3.040	38.042	0.002***	–2.321	0.764	–3.867	–0.775
Bread	Yes	3.862	0.0503	–1.571	310	0.059	–0.906	0.577	–2.041	0.229
	No			–2.682	44.989	0.005	–0.906	0.338	–1.586	–0.226
Mutton	Yes	0.053	0.818	1.305	310	0.096	0.811	0.621	–0.411	2.034
	No			1.274	29.449	0.106	0.811	0.637	–0.491	2.113
Garlic-Flavored Sausage	Yes	4.123	0.043**	0.597	310	0.276	0.317	0.532	–0.729	1.364
	No			0.957	41.521	0.172	0.317	0.332	–0.352	0.987
Milk	Yes	1.581	0.210	1.794	310	0.037**	1.127	0.628	–0.109	2.363
	No			2.420	35.162	0.010	1.127	0.466	0.182	2.073
Kasar Cheese	Yes	3.737	0.054	0.815	310	0.208	0.517	0.635	–0.732	1.767
	No			1.497	50.245	0.070	0.517	0.346	–0.177	1.212
Egg	Yes	0.003	0.954	–1.157	310	0.124	–2.100	1.815	–5.671	1.472
	No			–1.139	29.555	0.132	–2.100	1.843	–5.866	1.667
Butter	Yes	0.403	0.526	1.175	310	0.120	0.673	0.573	–0.454	1.801
	No			1.431	32.787	0.081	0.673	0.470	–0.284	1.631
Sun-Flower Oil	Yes	0.416	0.519	–0.813	310	0.209	–0.624	0.768	–2.136	0.887
	No			–1.089	34.983	0.142	–0.624	0.574	–1.789	0.540
Tomato	Yes	2.285	0.132	2.110	310	0.018**	10.046	4.760	0.679	19.413
	No			1.742	27.940	0.046	10.046	5.767	–1.769	21.861
Onion	Yes	0.401	0.527	1.489	310	0.069	4.068	2.733	–1.309	9.445
	No			1.897	33.749	0.033	4.068	2.145	–0.291	8.428
Dry Bean	Yes	0.829	0.363	–0.971	310	0.166	–0.753	0.776	–2.280	0.774
	No			–1.103	31.517	0.139	–0.753	0.683	–2.145	0.638
Lentils	Yes	2.770	0.097	–0.608	310	0.272	–0.552	0.908	–2.338	1.234
	No			–0.847	36.101	0.201	–0.552	0.651	–1.873	0.769
Olive	Yes	0.352	0.553	0.777	310	0.219	0.294	0.378	–0.451	1.038
	No			0.827	30.531	0.207	0.294	0.355	–0.431	1.019
Tea	Yes	2.580	0.109	1.213	310	0.113	0.932	0.768	–0.580	2.443
	No			0.991	27.865	0.165	0.932	0.940	–0.995	2.858
Fruit Juice	Yes	4.572	0.033**	–0.839	310	0.201	–0.415	0.495	–1.389	0.558
	No			–1.306	40.115	0.100	–0.415	0.318	–1.058	0.228
Men's Footwear	Yes	7.933	0.005***	–1.527	310	0.064	–1.731	1.134	–3.962	0.500
	No			–2.355	39.759	0.012**	–1.731	0.735	–3.217	–0.245
Men's Sport Shoes	Yes	5.752	0.017**	–1.127	310	0.130	–0.905	0.803	–2.486	0.675
	No			–1.850	42.684	0.036**	–0.905	0.489	–1.893	0.082
Women's Footwear	Yes	2.501	0.115	–1.151	310	0.125	–1.526	1.325	–4.134	1.082
	No			–1.363	32.232	0.091	–1.526	1.120	–3.806	0.754
Women's Sport Shoes	Yes	5.669	0.018**	–1.322	310	0.094	–1.094	0.828	–2.723	0.535
	No			–2.035	39.668	0.024**	–1.094	0.538	–2.181	–0.007

Note: *** and ** implies that the difference is significant at 1% and 5% level, respectively.
Source: Authors' calculation

Table A7 T-test results of means of increase rates of prices, 3 months: Shaban, Ramadan, Shawwal – others
A. Group statistics

3 Months (Shaban, Ramadan, Shawwal) – others		N	Mean	Std. Deviation	Std Error Mean.
Ind_Food	Mth_8-10	78	2.639	2.915	0.330
	Others	234	1.716	2.990	0.195
Ind_Clothing-Footwear	Mth_8-10	78	0.612	3.842	0.435
	Others	234	2.195	5.948	0.389
Rice	Mth_8-10	78	1.386	2.778	0.315
	Others	234	1.977	3.273	0.214
Dessert	Mth_8-10	78	2.278	2.021	0.229
	Others	234	1.925	1.985	0.130
Veal	Mth_8-10	78	2.979	2.574	0.291
	Others	234	1.693	3.038	0.199
Mutton	Mth_8-10	78	3.075	3.546	0.401
	Others	234	1.717	2.774	0.181
Milk	Mth_8-10	78	2.504	2.780	0.315
	Others	234	1.471	3.134	0.205
Butter	Mth_8-10	78	2.326	2.480	0.281
	Others	234	1.850	2.894	0.189
Tomato	Mth_8-10	78	9.071	23.687	2.682
	Others	234	2.741	23.097	1.510
Men's Trousers	Mth_8-10	78	0.903	3.962	0.449
	Others	234	2.070	7.503	0.490
Skirt	Mth_8-10	78	0.555	6.098	0.690
	Others	234	2.296	9.225	0.603
Women's Trousers	Mth_8-10	78	0.973	6.137	0.695
	Others	234	2.174	7.983	0.522
Men's Footwear	Mth_8-10	78	1.253	3.865	0.438
	Others	234	2.159	5.995	0.392
Men's Sport Shoes	Mth_8-10	78	1.436	2.794	0.316
	Others	234	2.161	4.222	0.276
Women's Sport Shoes	Mth_8-10	78	1.225	2.817	0.319
	Others	234	2.195	4.359	0.285
Bus Fare (Intra-Urban)	Mth_8-10	78	2.867	3.976	0.450
	Others	234	1.723	3.224	0.211

Source: Authors' calculation

Table A7 T-test results of means of increase rates of prices, 3 months: Shaban, Ramadan, Shawwal – others (cont'd)
B. T-test parameters

Indicator	Equal Variances Assumed?	Levene's Test for Equal. of Varian.		t-test for Equality of Means 3 Months (Shaban, Ramadan, Shawwal) – others						
		F	Sig.	t	df	Sig. (1-tailed)	Mean Diffe-rence	Std. Error Diffe-rence	95% Confidence Interval of the Difference	
									Lower	Upper
Ind_Food	Yes	0.039	0.843	2.377	310	0.009***	0.923	0.389	0.159	1.688
	No			2.407	135.003	0.009	0.923	0.384	0.165	1.682
Ind_ Clothing-Footwear	Yes	25.586	0.000***	–2.202	310	0.014	–1.583	0.719	–2.999	–0.168
	No			–2.714	205.807	0.004***	–1.583	0.583	–2.734	–0.433
Rice	Yes	1.050	0.306	–1.431	310	0.077	–0.591	0.413	–1.403	0.221
	No			–1.553	153.859	0.061	–0.591	0.380	–1.342	0.161
Dessert	Yes	0.724	0.395	1.353	310	0.088	0.353	0.261	–0.160	0.866
	No			1.341	130.066	0.091	0.353	0.263	–0.168	0.873
Veal	Yes	2.517	0.114	3.359	310	0.000***	1.287	0.383	0.533	2.040
	No			3.649	154.173	0.000	1.287	0.353	0.590	1.983
Mutton	Yes	4.141	0.043**	3.481	310	0.000	1.358	0.390	0.590	2.126
	No			3.083	110.105	0.001***	1.358	0.441	0.485	2.231
Milk	Yes	0.194	0.660	2.590	310	0.005***	1.033	0.399	0.248	1.817
	No			2.750	147.339	0.003	1.033	0.376	0.290	1.775
Butter	Yes	0.041	0.839	1.302	310	0.097	0.476	0.366	–0.243	1.196
	No			1.407	152.393	0.081	0.476	0.339	–0.193	1.145
Tomato	Yes	0.060	0.807	2.083	310	0.019**	6.331	3.039	0.351	12.311
	No			2.057	129.248	0.021	6.331	3.078	0.241	12.420
Men's Trousers	Yes	21.282	0.000***	–1.314	310	0.095	–1.167	0.889	–2.916	0.581
	No			–1.756	252.051	0.040**	–1.167	0.665	–2.477	0.142
Skirt	Yes	17.861	0.000***	–1.557	310	0.060	–1.742	1.119	–3.943	0.460
	No			–1.900	200.705	0.029**	–1.742	0.917	–3.549	0.066
Women's Trousers	Yes	4.157	0.042**	–1.214	310	0.113	–1.201	0.989	–3.147	0.746
	No			–1.382	170.436	0.084	–1.201	0.869	–2.916	0.515
Men's Footwear	Yes	15.197	0.000***	–1.249	310	0.106	–0.905	0.725	–2.331	0.521
	No			–1.541	206.204	0.062	–0.905	0.587	–2.063	0.253
Men's Sport Shoes	Yes	8.525	0.004***	–1.415	310	0.079	–0.725	0.512	–1.732	0.283
	No			–1.726	200.479	0.043**	–0.725	0.420	–1.552	0.103
Women's Sport Shoes	Yes	9.394	0.002***	–1.840	310	0.033	–0.970	0.527	–2.007	0.067
	No			–2.267	205.699	0.012**	–0.970	0.428	–1.813	–0.127
Bus Fare (Intra-Urban)	Yes	1.153	0.284	2.553	310	0.006***	1.144	0.448	0.262	2.025
	No			2.301	112.670	0.012	1.144	0.497	0.159	2.129

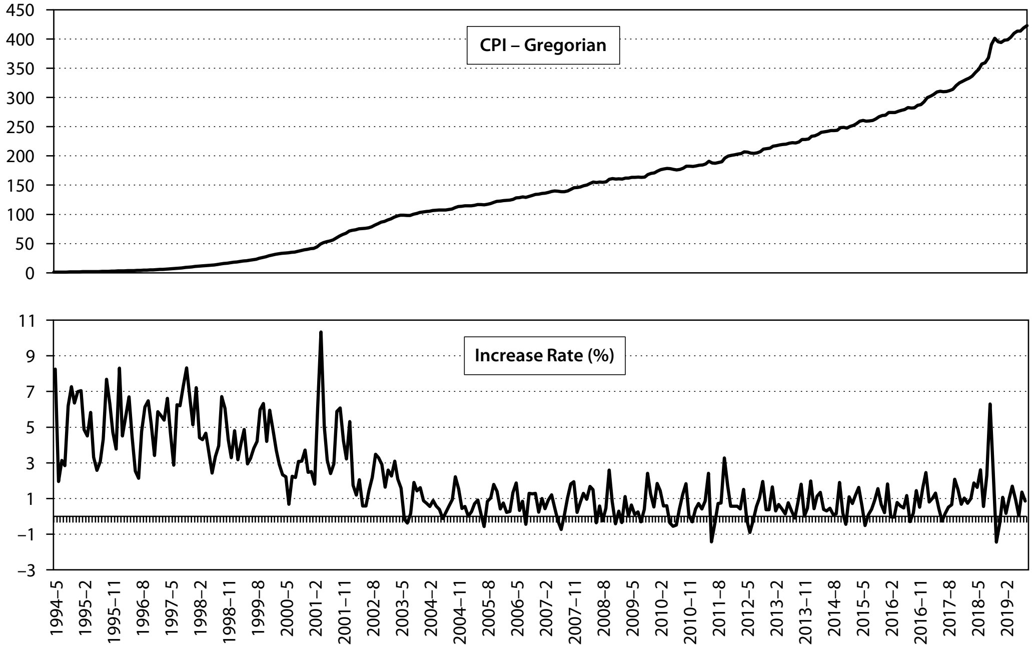
Note: *** and ** implies that the difference is significant at 1% and 5% level, respectively.
Source: Authors' calculation

Table A8 Monthly means of increase rates of production in 34 Hijri years and their ranks among months

Indicator		Monthly Means of Increase Rates in 34 Hijri Years (%)											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	C-Manufacturing	−0.54	1.61	1.11	0.97	0.90	0.83	0.17	−0.16	−1.42	0.44	2.38	0.21
2	B-Mining and quarrying	0.84	0.92	0.78	1.43	2.73	2.16	0.38	−0.90	−2.09	−0.84	−0.05	0.61
3	D-Electricity, gas, steam and air conditioning supply	−0.55	1.36	0.71	0.98	−0.10	0.72	1.31	1.58	0.94	1.42	0.18	−0.90
Indicator		**Rank of the Month (1:lowest, 12:highest)**											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	C-Manufacturing	2	11	10	9	8	7	4	3	1	6	12	5
2	B-Mining and quarrying	8	9	7	10	12	11	5	2	1	3	4	6
3	D-Electricity, gas, steam and air conditioning supply	2	10	5	8	3	6	9	12	7	11	4	1

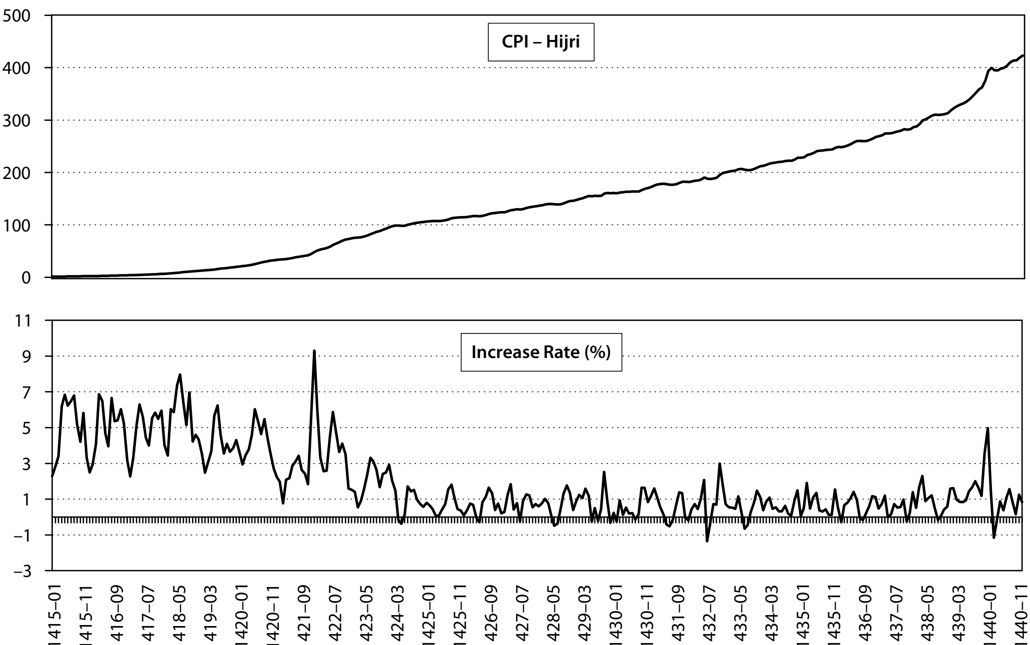
Source: Authors' calculation

Figure A1 CPI – Gregorian



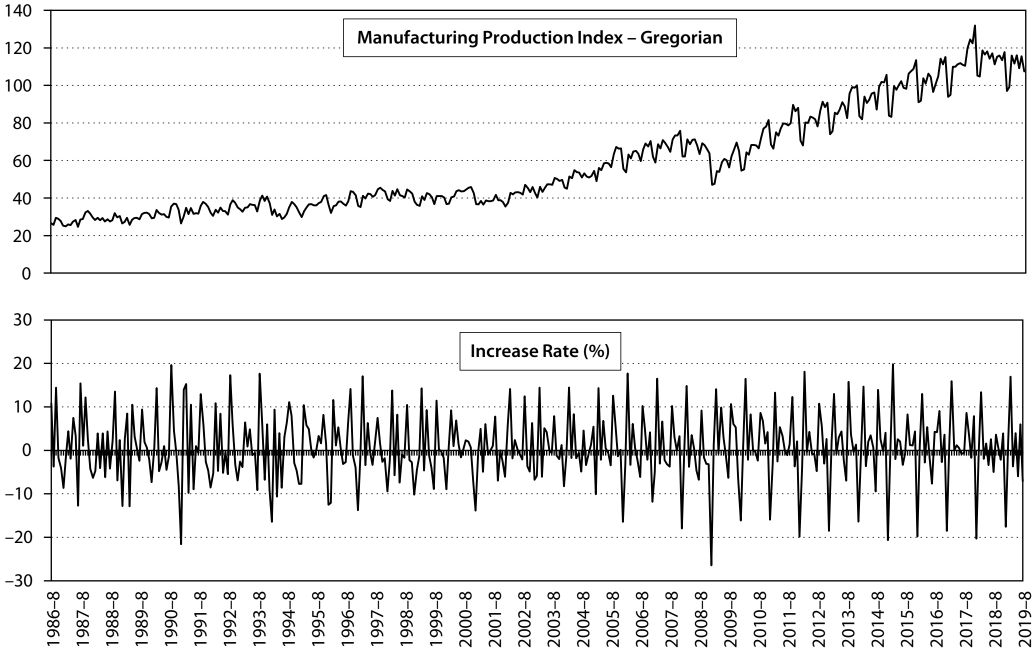
Source: Authors' construction based on TURKSTAT data

Figure A2 CPI – Hijri



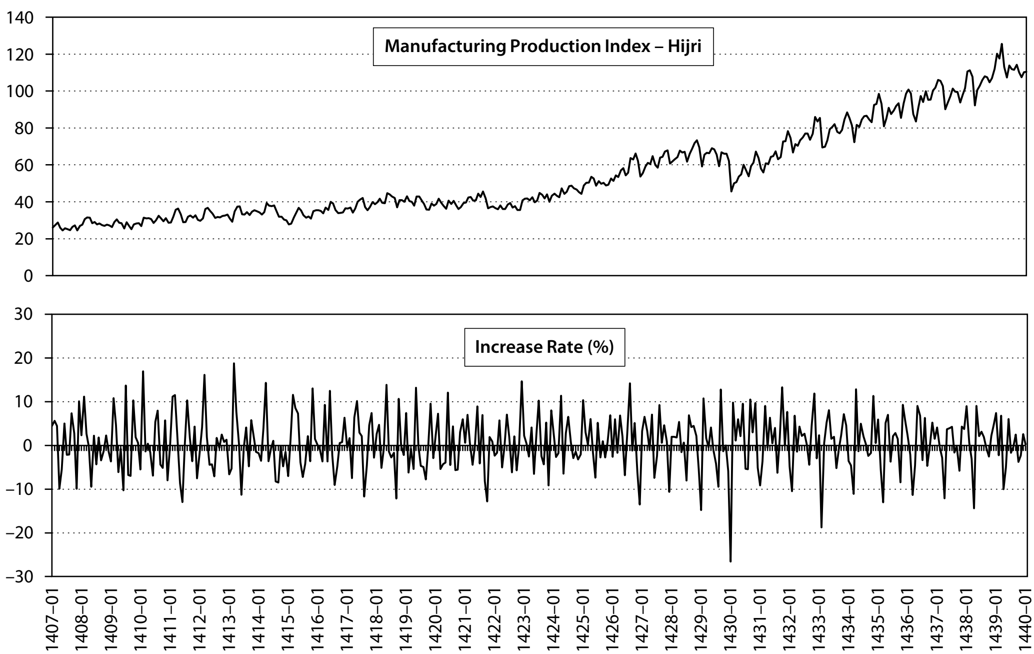
Source: Authors' construction

Figure A3 Manufacturing production index – Gregorian



Source: Authors' construction based on TURKSTAT data

Figure A4 Manufacturing production index – Hijri



Source: Authors' construction

Financial Development and Poverty Reduction in Crisis Periods: Panel Data Evidence from Six Countries of ECOWAS

Maroua Chaouachi [1] | *University of Tunis, Tunis, Tunisia*
Slim Chaouachi [2] | *University of Tunis, Tunis, Tunisia*

Abstract

In this study, we analyze the direct effect of financial development on poverty in crisis periods for a panel of Economic Community of West African States (ECOWAS) sample composed of six countries (Ivory Coast, Senegal, Gambia, Ghana, Mali and Benin) during the period 1996–2015, using econometric tests and static panel data. The main empirical result of this paper is that the financial development indicators and poverty proxies are significant and negatively correlated. The findings support the fact that financial development reduces directly poverty by increasing access for poor population to various sources of financing. As a result, finance makes transactions easier, provides opportunities for smoothing consumption and asset accumulation, and enables poor households to cope better with shocks, thus reducing the risk of recrudescence into poverty.

Keywords	***JEL code***
Poverty, financial development, crisis, panel data, econometric tests, ECOWAS countries	*I32, O16*

INTRODUCTION

The majority of empirical works focuses on the study of the effects of financial development on economic growth and abandons their direct effects on poverty. They argue that increasing national wealth reduces the poverty rate. Moreover, even if one agrees that financial development affects economic growth positively, it is unlikely that this growth will increase the incomes of the poor and reduce poverty accordingly.

The aim of this paper is to clarify the effects of financial development on poverty in times of crisis by proposing several estimation methods, based on a series of econometric tests. We consider this paper

[1] Higher Institute of Management, University of Tunis, Street of Liberty, Bouchoucha Bardo, 2000 Tunis, Tunisia. E-mail: marwa_ch@yahoo.fr.
[2] Department of Economics, Higher Institute of Management of Tunis, University of Tunis, Tunis, Tunisia. E-mail: chaouachislim@yahoo.fr.

an in-depth empirical assessment of the direct relationship between financial development (banking and monetary systems) and poverty. We use panel data modeling as well as time series and cross sectional studies. The panel data analysis relates mainly to heterogeneity among individuals. In other words, it allows us to examine the behavioral diversity of agents.

1 LITERATURE REVIEW

1.1 Theoretical literature

In the economic literature, the arguments that can justify the direct impact of financial development on poverty are of the order of three: the McKinnon conduit effect, the Shaw intermediation effect and the thresholds effect.

McKinnon (1973) initially suggested the conduit effect. In explaining this effect, McKinnon states that when the poor enter the financial system as savers, the conduit effect is likely to have a reducing impact on financial development for the well-being of the poor. McKinnon assumes that the investment is indivisible. This hypothesis is verified since "small peasants or poor artisans" form the representative economic units in the McKinnon study. In addition, investor-savers have limited access to external financing. Any prior accumulation (savings), in the form of real assets or cash balances, always precedes any expenditure devoted to investment. Thus, self-financing represents itself as the capital source of the investment of the poor.

Shaw (1973) pioneered the theory of the "Intermediation effect". Financial deepening helps to facilitate access to credit for the poor and can therefore benefit from it. Shaw's studies have found that an increase in the interest rate of deposits stimulates savings. In this case, the banks can reap significant savings and therefore they give more credit to investors whose poor can benefit. Thus, investment, which is, financed externally, increases.

The thresholds effect is based on the following assumption: "As the financial system grows, it may expand its services to the poor". In other words, assuming that the financial system grows, the result is that poor's access to financial services becomes more and more profitable. Thus, in order to extend these services to the poor in an efficient and competitive way, it is essential that the financial system reaches a certain threshold of development (e.g. Aghion et al., 2005). In developing countries where the financial system is not sufficiently developed, the poor moves towards the non-formal financial system and ousts the formal financial system. As a result, three major factors hinder their access to formal credit markets and/or financial services: the lack of acceptable or sufficient guarantees, the physical constraints and the lack of financial institutions specializing in financial services offered to the poor.

In summary, theoretical arguments presage three direct effects of financial development on poverty reduction. These effects are the McKinnon conduit effect, the intermediation effect of Shaw and the effect of the thresholds. If the McKinnon conduit effect and the effect of the thresholds require measures to free financial systems from constraints and restrictions that handicap their development in the supply of financial services to the poor (Kpodar, 2004), the intermediation effect of Shaw requires putting implementation of these measures within well-defined deadlines. In addition, other empirical studies complete these theoretical works.

1.2 Empirical literature

Tunjung et al. (2019) define poverty as a condition in which people are below the poverty line. This concept is the subject of numerous studies in different time segments (Aleksandrovna Kormishkina et al., 2018). According to the direct linkage between financial development and poverty alleviation in developing countries, it is one of the most discussed and acute scientific issues that was dealt with in intense researches. However, results are mixed and controversial across data, countries and methodologies of estimation. Hence, two views are as follow:

First, financial development is conducive in poverty reduction. Jalilian and Kirkpatrick (2002), and Beck et al. (2007) find that the degree of financial intermediation has a positive impact on the income of the poor. Jalilian and Kirkpatrick (2002) use the GDP rate of return to interpret the payment process in a low-income sample. Beck et al. (2007) focus on developing countries and the role of finance measured by the ratio of private sector credit as a percentage of GDP. Kpodar (2004) indicates that the financial development (proxied by the liabilities of financial institutions in the proportions of GDP, the transactions of commercial banks in GDP and the credit in the private sector in GDP) are likely to reduce absolute poverty or the income of the 20% poorer from 1988 to 1997. Using money supply (M2) as a percentage of GDP, Odhiambo (2009) concludes that financial development in the sense of Granger involves poverty reduction in South Africa. Guillaumont-Jeanneney and Kpodar (2011) declare that financial development is beneficial for the reduction of poverty only through the Conduit Effect of McKinnon. For example, the study finds that positive relationship exists between financial development (as measured by Liquid liabilities M3 as percentage of GDP) and poverty. Nevertheless, if the ratio of private credit to GDP is employed as financial development proxy, the linkage turns out to be statistically insignificant. Their empirical results indicate that the poor can benefit mainly from the banking system through the ease of transactions and the offer of savings opportunities at the expense of better access to credit. Perez-Moreno (2011) observes that financial development (as measured by liquid assets of the financial system to GDP ratio or by money and quasi money to GDP ratio) reduces the moderate poverty in the period of the 1970s–1980s. However, his analysis does not find evidence to support this last hypothesis for the period of the 1980s–1990s or when he uses the ratio of the value of credits granted by financial intermediaries to the private sector to GDP as measures of financial development, whereas they seem to be strengthened when he employs financial development's summary measures. Furthermore, the consequences do not found any Granger causality from poverty to financial development. Salah Uddin et al. (2012) examine empirically the long-run and causality relationship that exist between financial development and poverty in the case of Bangladesh for the period 1976–2010. Applying an ARDL co-integration approach, the evidence indicates that there is a long-term relationship between the development of the banking sector and the reduction of poverty. It is also observed that the causal linkage is bidirectional between banking sector development and poverty reduction. In the same spirit, Khan et al. (2012) employ the ARDL bounds testing the approach to co-integration to investigate the linkage between financial development and poverty in the Pakistan context using several indicators of financial development over the period during 1981–2010. The survey findings suggest that financial development contributes to poverty reduction. Focusing in 28 Indian states, Inoue and Hamori (2012) find similar results concerning credits and deposits. The research of Boukhatem and Mokrani (2012) deals with direct effects of financial development on poverty reduction in 67 low and middle income countries using data for the period of 1986–2009. The econometric analysis proves the existence of direct effects of financial development and poverty reduction. Using an innovative empirical technique based on ARDL co-integration with Structural Breaks and quarter frequency data in time period of 1975 to 2011 in Bangladesh, research conducted by Salah Uddin et al. (2014) finds significant poverty-reduction impact of financial development, but it is not linear. Chemli (2014) states that private credit relative to GDP is positively associated with lower poverty in Algeria, Iran, Jordan and Tunisia during the period between 1990 and 2012.The ARDL model is used to examine the relationship between variables. Quartey (2005) and Odhiambo (2010) endorse similar results for Ghana and Zambia. Abosedra et al. (2015) attempt to study the long-run relationship between financial deepening and poverty reduction by applying the Structural Break Autoregressive Distributed Lag-Bounds testing technique in Egypt between 1975Q1–2011Q4. Authors employ Zivot-Andrews unit root test in the presence of structural break to discuss the stationarity of series. Their research reports two major findings according to direct effects: (1) Domestic credit to private sector by bank (as percentage of GDP) contributes significantly to alleviate poverty; (2) Financial development contributes directly to facilitate the access or broad the access of the poor to financial services such as insurance-risk and domestic credit. Sehrawat and Giri (2016) attempt to analyze the relationship between financial sector and poverty in the case of India for the period 1970 to 2012 applying also an ARDL model. The empirical results support the claim that financial development affects negatively poverty reduction in both long-run and short-run. Causality test reveals a positive and unidirectional causality from financial development prevalence's measure to poverty reduction. Donou-Adonsou and Sylwester (2016) apply the instrumental variables approach in a panel of 71 developing countries for the period of 2002–2011. Estimation results from an impact evaluation show that banks reduce poverty when the incidence is reduced, and this when the private credit ratio as a percentage of GDP is used as proxy of financial development. On the other hand, by using microfinance institutions (MFIs) as a financial development measure, this indicator does not appear to have the negative impact on poverty. Results imply that banks have some ability to reduce poverty, MFIs do not. Boukhatem (2016) extends the work of Boukhatem and Mokrani (2012) and tries to identify and quantify the channels through which financial development influences poverty applying GMM-system estimation. The analysis is carried out on 67 low and middle-income countries provinces from 1986 to 2012. His paper's results showed that financial development played an important role in declining poverty, and this, independently of the econometric methods applied. Furthermore, the findings of the study found evidence that the instability of financial development would penalize the poorest people and would eradicate the positive impact of financial development. Covering annual observations of a sample of 42 Sub-Saharan African countries for the period 1980–2012, Zahonogo (2017) formulates the System Generalized Method-of-Moment (GMM) to highlight the linkage between financial development and poverty indicators, after controlling country specific effects and endogeneity. For this purpose, the research adopted poverty headcount and poverty gap as proxies of poverty and private credit as proxy of financial development. All variables used are transformed into natural logarithm. Author shows the existence of a certain threshold of financial development below which financial development has harmful effects on sub-Saharan African poor people and above which it could be related with less poverty. In addition, he promises and upholds the idea that the relation between financial development and poverty may be nonlinear. Rewillak (2017), by dividing financial development into four sub-categories and employing GMM panel regression in developing countries over the period 2004–2015 shows both financial deepening and greater physical access are beneficial in diminishing the percentage of households below the poverty line. Author adds that financial instability (fragility) has not a harmful impact on poverty alleviation. In a 2019 study conducted in Indonesia from the1980–2014 periods, the financial depth measured by credit volume affects negatively the rural poverty by using an ARDL approach to co-integration and Granger causality based on the VECM test. More especially, results show that there are both long-run and short-run relationships among the variables in the model. Additionally, findings for direction of causal relationship indicate that a bi-directional causality exists between the financial sector and poverty (Majid et al., 2019). A recent research employing Instrumental variable regressions in 15 Indian states from the 1983–2005 periods, suggests that financial depth post-1991 (as measured by credit volume) reduces rural poverty by fostering entrepreneurship and incorporating geographic-sectoral migration (Ayyagari et al., 2020). Using a Multiple Correspondence Analysis to generate a financial inclusion index, and Three-stage Feasible Least Squares to estimate households' vulnerability to poverty in Ghana, research conducted by Koomson (2020) finds two major effects of financial inclusion on poverty. Financial inclusion is linked to a diminishing in a household's probability of being poor. The drop of this probability is capped in 27%. Likewise, it avoids the exposure of a household to future poverty of around 28%. Yet, the negative impact of financial inclusion on alleviation poverty and vulnerability to poverty is more important in rural than in urban areas and when households are derogated by women than men. Policymakers should be more responsive to enhance financial inclusion in developing countries.

In contrast, some evidence proves that financial development does not affect poverty. Fowowe and Abidoye (2012) use a private credit as a financial development measure and examine its effects on poverty in a sample of countries in sub-Saharan Africa. Their empirical results show that this indicator of financial development has not a significant influence on poverty in these countries. Yet, macroeconomic variables such as the rate of trade openness and low inflation lightened poverty level. By applying an Autoregressive Distributed Lag (ARDL) model in Nigeria for annual series covering the period from 1970 to 2011, Dandume (2014) points out that financial sector development does not involves the poverty reduction. This can be explained by the fact that an increase in the supply of loan able funds due to financial sector development is not enough to reduce the poverty. As a result, strong measures seem to be needful. More recently, research carried out by Ayad (2018) resorts to the regime shift analysis for both unit root tests with structural breaks and Hensen co-integration test in order to detect the long-run and short-run elasticities between poverty (as measured by the consumption per capita) and financial development (as measured by the sum of total external liabilities and total external assets divided by GDP) in Algeria in the period between 1970–2017. Findings prove that there is a long-run relationship among the poverty and financial development with a regime shift in 2009, and financial development is not able to decrease the poverty.

Our contribution in this study is empirical. The theoretical and empirical literatures mentioned above provide the rationale for our consideration of the direct effects of financial development on poverty alleviation.

2 DATA AND METHODOLOGY

2.1 Presentation of data and model

Data were extracted from the World Bank (World Development Indicators, 2016) spanning the period 1996–2015. Our original purpose was to insert all ECOWAS countries, but all data are available only for 6 countries (Ivory Coast, Senegal, Gambia, Ghana, Mali and Benin). Beside, the number of observations is expected to be similar across countries leading to estimations over a balanced panel data. A number of missing observations characterizes poverty data.[3] In order for the balanced databases to be complete (Bangoura et al., 2016), we have tried to fill the gaps by using a simple extrapolation method on the previous or historical value. According to Little and Rubin (2002), if the percentage of missing values for a variable was up to 5%, the values cannot be excluded or deleted. Hence, it is essential to change each missing value by an imputed value.

Our econometric model with panel data is inspired by the studies of Kpodar (2004) and Guillaumont-Jeanneney and Kpodar (2011) in which the poverty indicator is regressed on the indicator of financial development and a set of variables of control presented by the following expression:

$$PV_{it} = \alpha_i + \alpha_0 + \alpha_1 FD_{it} + \alpha_2 Ln(Y)_{it} + \alpha_3 crisis + \alpha_4 INF_{it} + \alpha_5 OPN_{it} + \alpha_6 GINI_{it} + \alpha_7 GV_{it} + \alpha_8 UNP_{it} \\ + \alpha_9 EDU_{it} + \alpha_{10} HEL_{it} + \alpha_{11} TEL_{it} + \varepsilon_i \, , \tag{1}$$

where: PV_{it} refers to the indicators of poverty presented by the headcount poverty and the poverty gap, respectively. Headcount poverty (PV1) denotes the proportion of population living below the international poverty line of 1.9$ a day following Honohan (2004). Poverty gap (PV2) measures the average distance between the income of the poor population and the poverty line. According to Guillaumont-Jeanneney and Kpodar (2011), this last indicator makes it possible to determine the extent to which poor populations are below or above the poverty line.

[3] <http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx>.

FD_{it} is the level of financial development including banking and monetary variables. Money supply to GDP ratio (M3) measures the liquidity's degree of the financial system, presented by the "McKinnon Conduit Effect". To measure bank development, we use the variable (CB) which equals the domestic credit provided by the banking sector divided by GDP. We use also private credit (CP) which equals the value of credits by financial intermediaries to the private sector divided by GDP following Levine and Zervos (1998), Rousseau and Wachtel (2000), and Beck and Levine (2004). In general, (M3) and (CP) are commonly used in empirical studies to estimate the impact of financial development on poverty (e.g. King and Levine, 1993; Levine et al., 2000; and Kpodar, 2006).

On the other hand, we introduce the natural logarithm of GDP per capita ($Ln\ (Y)_{it}$) which controls the impact of economic growth on poverty, following Beck et al. (2006).

To account for periods of financial instability, we include the recurrence of crisis (crisis). It is a dichotomous variable that takes the value of 1 in the period of crisis and 0 otherwise. We take into account crises that started from 1996 to 2015: the Asian crisis (1997), the Russian crisis (1998), the Brazilian crisis (1998–1999), the crisis of Turkey (2000), the stock market crash of 2001–2002, the economic crisis of Argentina (2001), the attacks of September 11 (2001) in the United States, the Brazilian crisis (2002), the global financial crisis: "subprime" crisis (2007–2009) and finally the Greek crisis (2009). We consider the extreme form of financial instability (e.g. Chemli and Smida, 2013).

Inflation rate (INF_{it}), measured by the consumer price index and reflects the effect of macroeconomic stability on poverty.

Rate of trade openness (OPN_{it}) measured by the ratio of the sum of exports and imports of goods and services to GDP and reflects the trade integration policy on poverty.

Inequality index ($GINI_{it}$) measures the inequality of income distribution. It ranges from 0 (distribution is uniform and perfectly equal, where households have the same income) to 1 (where distribution is perfectly unequal).

GV_{it} denotes the ratio of government consumption to GDP. Various practitioners use this variable as a control variable for government intervention.

In order to capture the effect of the labor market on poverty, we use the rate of the Unemployment (UNP).

Additional control variables that include the ratio of public expenditure in education to GDP (EDU_{it}) and the ratio of public expenditure in health to GDP (HEL_{it}) to capture the impact of human capital investment on poverty (e.g. Agénor, 2003).

Last, we include the infrastructure indicator (TEL_{it}), measured by the number of telephone line (by 100 capita).This indicator contributes both to the economic growth and to the improvement of the population's living standards.

Finally, α_i is an unobserved country specific effect ε_i is the error term with $E(\varepsilon_{it} = 0)\forall i, t$, i is the county and t is the time period.

2.2 Econometric methodology

Before the implementation of our econometric model, we verify the homogeneity or heterogeneity of the data generating process. Econometrically, it comes down to testing whether the coefficients of the model retained are equal in the individual dimension. We test the overall homogeneity of behaviors (constants) in time and space with the Fischer test. In the case where the sample is totally homogeneous, we use the OLS on panel data. In the case of heterogeneous behaviors, we choose between the Fixed Effect Model and the Random Effect Model according to the results obtained by the Hausman (1978) specification test. If the model to be retained is a Fixed Effect Model or Random Effect Model, we use then the Wooldridge (2002) autocorrelation test, if not, our estimators will be biased. Thus, if the errors are autocorrelated, we apply Baltagi and Wu (1999) first-order autocorrelation correction method to reduce this potential bias. We test the heteroscedasticity of the errors with Breush-Pagan (1979) test. Such heteroscedasticity is then corrected by the method of White (1980). If the errors are both heteroscedastic and autocorrelated, we use the Quasi Generalized Least Squares (MCQG) method. Dutta and Osei-Yeboah (2008) have used this method, in particular. We suspect endogeneity of the explanatory variables, we refer to the test of Nakamura-Nakamura (1981). Finally, we discuss the results obtained.

3 RESULTS AND DISCUSSIONS

From the Correlations Table 1 between poverty proxies and financial development indicators, it can see that all Pearson's correlations coefficients are negative.

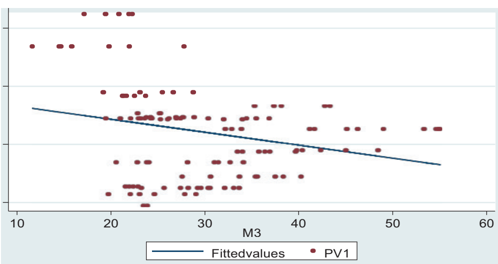
Table 1 Correlation between poverty and financial development indicators

	PV1	PV2	M3	CB	CP
PV1	1.0000				
PV2	0.9412*(0.0000)	1.0000			
M3	−0.2573*(0.0046)	−0.2859*(0.0016)	1.0000		
CB	−0.4920*(0.0000)	−0.4143*(0.0000)	0.7382*(0.0000)	1.0000	
CP	−0.2405*(0.0081)	−0.2994*(0.0009)	0.5208*(0.0000)	0.3848*(0.0000)	1.0000

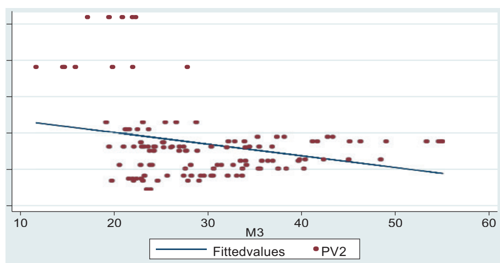
Notes: * indicates statistical significance at 1%. Numbers in parentheses under the coefficients are p-values.
Source: Data processing by using STATA 12

Turning to the correlation between financial development indicators, there is a positive and significant correlation between them. Furthermore, values are at high levels. In fact, this suggests that these indicators capture the same information. We register also the highly positive correlation between the money supply to GDP ratio and the domestic credit provided by the banking sector to GDP ratio (0.7382). As shown by Kpodar (2006), financial development indicators are negatively correlated with poverty and positively correlated with each other.

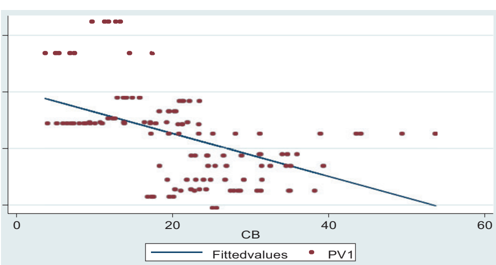
Figure 1 Graphs between poverty and financial development



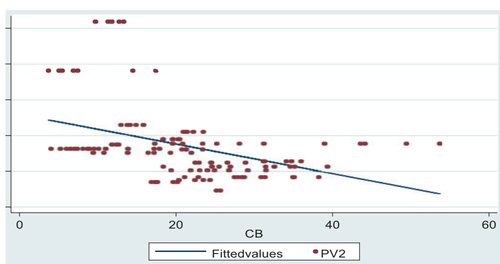
Relationship between headcount poverty and money supply to GDP ratio



Relationship between poverty gap and money supply to GDP ratio

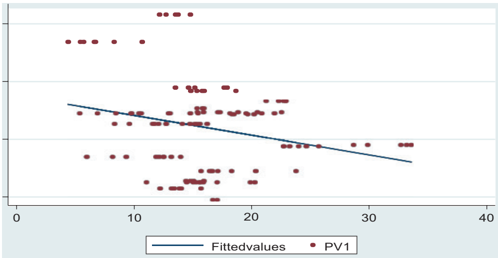


Relationship between headcount poverty and domestic credit provided by the banking sector divided to GDP

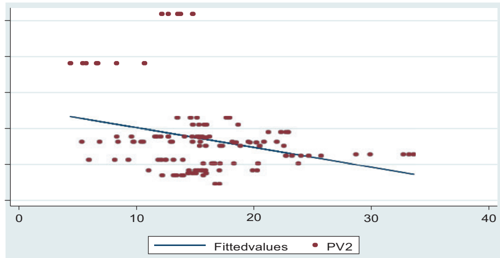


Relationship between poverty gap and domestic credit provided by the banking sector divided to GDP

Figure 1 continuation



Relationship between headcount poverty and credits by financial intermediaries to the private sector divided to GDP



Relationship between poverty gap and credits by financial intermediaries to the private sector divided to GDP

Source: World Bank and PovcalNet, formulated by authors

Figure 1 illustrates the relationship between headcount poverty and financial development, also the relationship between poverty gap and financial development. We can note that financial development indicators do not favor the two indicators of poverty, with a mighty descending slope which crosses the group of points. A negative impact of the financial development indicators on the two indicators of poverty can be established.

Table 2 Results of Fischer test of global homogeneity

Endogenous variable : PV1	M3	CB	CP
F	F(16,103) = 4.95	F (16,103) = 5.33	F(16,103) = 5.11
Prob >F	0.0000	0.0000	0.0000
Endogenous variable : PV2	**M3**	**CB**	**CP**
F	F(16,103) = 8.16	F(16,103) = 8.82	F (16,103) = 8.21
Prob >F	0.0000	0.0000	0.0000

Source: Data processing by using STATA 12

Firstly, we begin with testing of global homogeneity. The results are shown in Table 2. Indeed, the probability of the Fischer test for the headcount poverty and the poverty gap is close to zero. Therefore, we reject the null hypothesis of the total homogeneity of the constants. On the other hand, we accept the model with individual specific effects (Fixed Effect Model or Random Effect Model). Before proceeding with discussions of the results of estimation, we carry out a set of tests in order to perceive the possible problems that may persist on the data. We examine whether the autocorrelation and the heteroscedasticity across errors. Yet, we carry out the Nakamura-Nakamura test in order to control the endogeneity bias.

Table 3 Results of Wooldridge test of autocorrelation

Endogenous variable : PV1	M3	CB	CP
F	F(1,5) = 1.625	F (1,5) = 43.777	F(1,5) = 6.600
Prob >F	0.2584	0.0012	0.0501
Endogenous variable : PV2	**M3**	**CB**	**CP**
F	F(1,5) = 2.478	F(1,5) = 27.536	F (1,5) = 6.747
Prob >F	0.1763	0.0033	0.0484

Source: Data processing by using STATA 12

Results of the Wooldridge test[4] for the variable M3 show that the null hypothesis of no autocorrelation in order 1 is accepted at the 5% since the probability of this test is greater than 5% for the two poverty indicators. Consequently, we do not need to make such a correction. On the other hand, for the variable CB, the probabilities associated to the Wooldridge test are less than 5% for the two indicators of poverty. In this case, we take again the estimation of the Random Effect Model by using the method of Baltagi and Wu.[5] For the variable CP, we estimate the Random Effect Model by using the method of Baltagi and Wu for the poverty gap.

The results of the Breusch-Pagan of heteroscedasticity test show that all Breusch-Pagan statistics for the two indicators of poverty are greater than the tabulated value. Therefore the errors are heteroscedastic whatever the indicator of the financial development used.

Table 4 Results of Breusch-Pagan test of heteroscedasticity

Endogenous variable : PV_1	**M3**	**CB**	**CP**
R^2	0.6901	0.6893	0.6893
Khi2 calculated	82.812	82.716	82.716
Endogenous variable : PV_2	**M3**	**CB**	**CP**
R^2	0.6623	0.6632	0.6630
Khi2 calculated	79.476	79.584	79.56

Notes: Under a Chi-square law at k-1 degrees of freedom. N and R^2 are respectively the number of observations and the coefficient of determination of the model of step 3 and k is the number of explanatory variables including the constant. Tabulated Chi2 is 19.6751 for dd1 = 11 and α = 5%. *, **, *** indicate statistical significance respectively at 10%, 5% and 1%.
Source: Data processing by using STATA 12

Also, we carry out the Nakamura-Nakamura test in order to control the endogeneity bias. According to Kpodar (2004), the financial development variables, Ln (Y) and GINI can be suspected of endogenous to poverty indicators, in other words they can be correlated with the errors. To solve this problem, lagged financial development indicators of one period, lagged Ln (Y) variable of one period and lagged GINI of one period were chosen as instrumented variables. The Nakamura-Nakamura test results show that the endogeneity hypothesis has been rejected at 5%. As a result, the financial development variables (M3, CB and CP), Ln (Y) and GINI are not endogenous.

Table 5 Results of Nakamura-Nakamura test of endogeneity

Endogenous variable: PV_1	**M3**	**CB**	**CP**
Residue1 (associated to FD)	4.543012(0.130)	–1.465696(0.491)	26.8704(0.304)
Residue2 (associated to Ln(Y))	9.191219(0.188)	2.793045(0.174)	2.383958(0.132)
Residue3 (associated to GINI)	0.7156593(0.416)	–0.3834397(0.442)	2.43887(0.217)
Endogenous variable: PV_2	**M3**	**CB**	**CP**
Residue1 (associated to FD)	3.309656(0.120)	–0.6115025(0.673)	18.45365(0.303)
Residue2 (associated to Ln(Y))	8.393632(0.106)	2.49063*(0.099)	2.036284*(0.085)
Residue3 (associated to GINI)	–0.9033365(0.289)	–0.3970353(0.299)	2.049209(0.166)

Notes: * indicates statistical significance at 10%. Numbers in parentheses under the coefficients are p-values.
Source: Data processing by using STATA 12

[4] The Wooldridge test (2002) is programmed on the "xtserial" command. A second way to do the autocorrelation test is to proceed indirectly using the "xtregar" command.
[5] The method of Baltagi and Wu is preprogrammed on STATA 12 under the command "xtregar".

According to Table 6, the statistics of Hausman test for headcount poverty appear with a probability Prob > 5% for the three financial development indicators M3, CB and CP. Thus, we keep the Random Effect Model for the three indicators of financial development. It is globally significant with a zero probability of the Wald Chi2 test for the whole of specifications.

We conclude that the impact of financial development is always negative with significance varying with the nature of the measure introduced either for monetary development or for banking development. Individually, the coefficient associated to CB (Column 3) is negative and statistically significant with the high level of 1%. At this step, we can note that an increase of 1% of the money supply to GDP ratio will generate a decrease in headcount poverty of 0.233% (Column 1). For the domestic credit provided by the banking sector divided to GDP, an increase of 1% in this indicator will result a deterioration of the headcount poverty of 0.266% (Column 3). According to ratio of credits by financial intermediaries to the private sector to GDP, an increase of 1% will reduce the headcount poverty of 0.374% (Column 4). This last result is confirmed with the studies of Beck et al. (2007) which affirm that an increased credit to the private sector leads to a decline in people living below the poverty line.

Table 6 Direct impact of financial development on headcount poverty in ECOWAS: Static panel model results

Variables	REM	REM	REM with AR(1) disturbance	REM
	(1)	(2)	(3)	(4)
M3	−0.233*(0.060)			
CB		−0.261**(0.012)	−0.266***(0.010)	
CP				−0.374*(0.083)
Ln(Y)	−16.422*(0.084)	−14.974(0.109)	−15.302*(0.093)	−14.262(0.133)
crisis	0.991*(0.093)	0.898(0.131)	0.891(0.136)	0.837(0.165)
INF	−0.062(0.173)	−0.057(0.205)	−0.0568(0.211)	−0.063(0.167)
OPN	0.006(0.790)	−0.001(0.994)	−0.001(0.970)	0.002(0.911)
GINI	1.4***(0.000)	1.424***(0.000)	1.422***(0.000)	1.425***(0.000)
GV	−0.973*(0.075)	−0.942*(0.081)	−0.926*(0.085)	−0.905*(0.098)
UNP	0.517(0.161)	0.502(0.166)	0.498(0.168)	0.474(0.197)
EDU	0.457(0.398)	0.468(0.376)	0.477(0.366)	0.401(0.455)
HLT	−2.732**(0.003)	−2.783***(0.002)	−2.776***(0.003)	−2.846***(0.002)
TEL	−0.099(0.947)	−0.803(0.587)	−0.798(0.589)	−0.375(0.801)
Constant	−0.417(0.788)	0.02(0.990)	0.077(0.960)	−0.141(0.927)
Wald Chi2 test	77.95***(0.000)	82.54***(0.000)	82.61***(0.000)	77.10***(0.000)
Hausman test (Prob)	0.9944	0.9804		0.9414
Number of countries	6	6	6	6

Notes: *, **, *** indicate statistical significance respectively at 10%, 5% and 1%. Numbers in parentheses under the coefficients are p-values; REM indicates Random Effect Model. AR (1) indicates Durbin-Watson test for first order serial correlation.
Source: Data processing by using STATA 12

Similarly, Honohan (2004) finds a significant and robust impact of financial development (measured by the ratio of domestic credit to the private sector to GDP) on the headcount poverty. Its result suggests that there is a direct relationship between financial development and poverty eradication and that this relationship is independent of the indirect impact via the economic growth. In ECOWAS countries, the growth of the private sector generates employment opportunities through the creation of small and medium-sized enterprises (SMEs). Recently, several private sector studies from World Bank member countries have focused on the role of SMEs in the fight against poverty.

Generally, the results of this work reveal that SMEs help to reduce unemployment and thus contribute to alleviating household poverty. Additionally, Ayyagari et al. (2007) argue that low entry costs, easy access to finance, availability and dissemination of information lead to an increase in private firms in the manufacturing sector and that SMEs account for around 60% of employment in this sector.

In columns (1), (3) and (5) of Table 7, results suggest that the ratio of money supply to GDP ratio and the domestic credit provided by the banking sector to GDP are negative and significantly correlated with poverty gap. The effect of financial development on poverty reduction is more powerful in the case of the headcount of poverty than in the poverty gap. In fact, an increase in a point of the percentage of M3 reduces the poverty of 0.161%. These results support the McKinnon conduit effect. Likewise, an increase in CB from 1% will lead to a reduction of the poverty gap of 0.209%. In contrast to headcount poverty, CP is not significant. Therefore, financial development contributes directly to poverty reduction by improving the access of poor population to financial services, which is in conformity with theoretical analyzes and thus corroborate with empirical studies.

Table 7 Direct impact of financial development on poverty gap in ECOWAS: Static panel model results

Variables	REM	REM	REM with AR(1) disturbance	REM	REM with AR(1) disturbance
	(1)	(2)	(3)	(4)	(5)
M3	–0.161*(0.080)				
CB		–0.202***(0.008)	–0.21***(0.006)		
CP				–0.206(0.196)	–0.219(0.172)
Ln(Y)	–11.965*(0.088)	–11.004(0.109)	–11.423*(0.097)	–10.52237(0.134)	–11.349(0.109)
crisis	0.552(0.219)	0.496(0.255)	0.494(0.260)	0.442(0.320)	0.44(0.330)
INF	–0.049(0.145)	–0.045(0.168)	–0.045(0.175)	–0.049(0.147)	–0.048(0.164)
OPN	0.004(0.812)	–0.001(0.976)	–0.001(0.946)	0.001(0.930)	0.001(0.983)
GINI	1.565***(0.000)	1.585***(0.000)	1.583***(0.000)	1.578***(0.000)	1.574***(0.000)
GV	–0.793**(0.049)	–0.775**(0.050)	–0.754*(0.055)	–0.747*(0.065)	–0.713*(0.076)
UNP	0.253(0.352)	0.249(0.349)	0.244(0.355)	0.217(0.424)	0.213(0.431)
EDU	0.554(0.165)	0.584(0.132)	0.597(0.123)	0.49(0.218)	0.503(0.205)
HLT	–1.839***(0.007)	–1.874***(0.006)	–1.876***(0.005)	–1.91***(0.006)	–1.911***(0.006)
TEL	-0.34(0.758)	–0.857(0.429)	-0.865(0.424)	–0.538(0.626)	-0.534(0.628)
Constant	–0.174(0.878)	0.155(0.890)	0.209(0.855)	–0.009(0.993)	0.081(0.946)
Wald Chi2 test	130.26***	138.80***	139.32***	127.26***	126.96***
Hausman test (Prob)	0.9933	0.9758		0.9497	
Number of countries	6	6	6	6	6

Notes: *, **, *** indicate statistical significance respectively at 10%, 5% and 1%. Numbers in parentheses under the coefficients are p-values. REM indicates Random Effect Model. AR (1) indicates Durbin-Watson test for first order serial correlation.
Source: Data processing by using STATA 12

In Tables 6 and 7, results of estimation of the direct impact of the money supply on GDP ratio and domestic credit provided by the banking sector to GDP ratio on headcount of poverty and poverty gap suggest that the growth rate of the GDP per capita is negative and statistically significant at 10%.

The hypothesis of a negative effect of economic growth on the poverty is not rejected. In addition, Ahmad and Riaz (2012), and Inoue and Hamori (2012) argue that economic growth is an instrument of poverty alleviation. However, this positive effect can be hindered and slowed down by the presence of income inequalities. Šhare and Oržiklas Druežta (2016) conclude that economic growth is good for poverty reduction but it is not enough. Keho (2017) reveals bidirectional long-run causality between the two phenomena. As Guillaumont-Jeanneney and Kpodar (2006), the indicator of financial instability, measured by the dummy variable (crisis) has a positive effect on poverty. In some developing countries, setting up safety nets such as social assistance programs, conversion aids, etc can reduce the negative effect of financial instability and especially the effect of banking crisis. With regard to the variable (INF) which captures the effect of macroeconomic stability on poverty, it has a negative sign but its coefficients are not significant at conventional levels. Results are in conformity with those found by an abundant number of economists, such as Levine and Renelt (1992), Fisher (1993), Baldacci et al. (2002), and Enami and Lustig (2018), who argue that the relationship between inflation and poverty is negative. Similarly, Dollar and Kraay (2002) show that the impact of the inflation rate on the income of the poorest 20% population is negative. Inflation is a factor which can erode purchasing power, makes false the expectations of agents, attenuates the value of assets and penalizes relatively more the poor since their assets are not indexed to inflation. Furthermore, high inflation hampers countries' economic convergence. On the other hand, by introducing the variable OPN, we notice that coefficients are sometimes positive, sometimes negative with indicators of poverty. Inoue and Hamori (2012) agree that trade openness helps to eradicate poverty in developing countries. In addition, Basanta and Malvika (2014) find that poverty is significant and negatively correlated with total trade, exports imports and merchandise trade. However, the surprising positive sign of trade openness may, however, be explained by the risk of a broad opening to foreign capital flows. A second explanation relates to the fact that financial globalization is likely to increase income inequality when only some countries take advantage of its favorable effects. In addition, the coefficient associated to the GINI index is positive and statistically significant at a high level, reflecting the positive effect of the income inequality index on poverty found by Bamba (2001), Meng et al. (2005), and Zaman et al. (2020) who note empirically that there is a positive relationship between poverty and the level of inequality income, adding that a high inequality can increase poverty. Similarly, this result is corroborated by studies of Ravallion (2005), and Mchiri and Moudden (2011), who affirm that high inequality can deteriorate the situation of the poor. Unemployment (UNM) contributes positively to reducing poverty. Thus a 1% increase in unemployment leads to an increase of poverty. By introducing the variable (GV) that represents public expenditure (% of GDP), the results of different estimations indicate that only all coefficients associated to this variable is statistically significant at 1%. With regard to education expenditure (EDU), the results show that there is a positive and surprising relationship between this variable and poverty indicators. In other hand, we find that health expenditure (HEL) is negative and significantly correlated with poverty at 1%. An increase in spending on health helps to reduce headcount poverty and poverty gap. According to Castro-Leal et al. (2000), the solution is not only to increase budgets for health but also to break down all the constraints that prevent poor of benefiting from social services subsidies. In order to examine the impact of infrastructure on poverty, we introduce the variable (TEL). All coefficients allotted to this variable are negative but lacked of significance. In fact, this indicator of infrastructure can essentially affect the quality of life of poor (Chemli and Smida, 2013). Infrastructure plays a crucial role in the development process. It not only helps to connect operators to markets, reduce factor costs and improve the competitiveness of the economy, but provides also the services to the poor and determines their quality of life. In addition, this indicator promotes both economic growth and improves the standard of living of population. Guillaumont-Jeannenney and Kpodar (2005) affirm this result by revealing that a high road density may reduce poverty.

CONCLUSION

Using a sample of six ECOWAS countries from 1996 up to 2015 for the periods of crisis, this paper tries to investigate the relationship between financial development and poverty. It tests the direct impact of both monetary system and bank system on poverty. Generally, we report using static panel and across different control variables that the financial development is important or even detrimental for poverty reduction in the ECOWAS countries. As a matter of policy implications, it's obvious to promote the development of financial systems. In order to affect poor population favorably, financial development must provide them better access to financial services (loans, deposits, insurance, etc.) so that the McKinnon capital effect and the intermediation effect of Shaw intervene. Furthermore, policymakers must also consider the risks associated with crisis. Therefore, to encourage financial development polices to be accompanied by measures enhancing the stabilization of the macroeconomic environment. In ECOWAS countries, public authorities should mainly support the establishment and development of decentralized financial systems, especially microfinance institutions. Their main purpose is the provision of savings accounts and loans to the poor population. Firstly, these institutions are considered to be financial institutions that specialize in providing financial services to population with limited access to banking services. Secondly, these institutions can overcome the constraint of the absence of collateral by the mobilization of guarantee funds. Finally, since these micro-finance institutions are closer to the poor, they solve the problem of territory coverage of bank branches.

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Modelling Structural Relations for Tourism Demand: the Central European Cases

Lukáš Malec [1] | *University of Economics and Business, Prague, Czech Republic*
Václav Žák | *University of Economics and Business, Prague, Czech Republic*

Abstract

This application study concentrates on causal links, directed from economic parameters to internal Czech and Slovak tourism for both, short- as well as long-term changes in time series. As tourism forms a fundamental part of the service industry with many social and environmental connections, the structural equation modelling (SEM) methodology, i.e. simultaneous equations covering the number of fundamental and derived variables, is used. Taking into account the market specifics with relative close history, the identical models for countries are selected, enabling a precise mutual comparison. The data on a ratio of non-residents and residents, together with nights spent and other parameters, are examined for first as well as seasonal differencing. For instance, the destination living cost, relative wages and salaries, the balance of payments, labour productivity, trade openness and harmonized unemployment as exogenous variables, are introduced. Covering short and long horizons, labour productivity is a fundamental parameter in the Czech Republic. Significant relations proved differently between countries presented by trade openness as a factor of the global economy. The members of destination management or other authorities can appreciate the results, concentrated especially on various accommodation establishments and hospitality.

Keywords	***JEL code***
Structural equation modelling, causality, simultaneous equations, tourism	*C38, C50, Z30*

INTRODUCTION

Industrial production and manufacturing still present an important segment in the Czech Republic and Slovakia. However, many direct, indirect, and induced effects of tourism make it a significant contributor as well. Tourism is a very dynamic sector ranking globally third position behind the petrochemical and car industries in terms of volume of sales, employing a vast workforce. It represents a fundamental activity of society, connecting employment, retail, services, and many other fields in a variety of effects. According to the World Tourism Organization, tourism demonstrates resilience to geopolitical and global economic instabilities. The travel and tourism industry are important sectors of the economy, contributing 10.4% of world GDP (WTTC, 2019). It has created 319 million jobs worldwide,

[1] Department of Statistics and Probability, Faculty of Informatics and Statistics, University of Economics and Business, W. Churchill Sq. 4, 130 67 Prague 3, Czech Republic. Corresponding author: e-mail: lukas.malec@vse.cz.

representing roughly 1 out of every 10 jobs. The prediction for tourism is also positive despite recent global events. In tourism time series data, the econometric approaches of time-varying parameter models, error correction model and autoregressive distributed lag model have been widely adopted (Assaker, Vinzi, O'Connor, 2010; Song and Witt, 2000). Although the application of SEM is appropriate in tourism, with demand related to the determinants of consumer behaviour, such methodology is seldom applied. It is also suitable at an aggregate level due to causal links between a variety of variables related to supply and corresponding demand.

Tourism generally supports foreign exchange earnings, it promotes investment (Krueger, 1980; Balaguer and Cantavella-Jorda, 2002) and introduces an economy of scale that decreases local production costs and reduces unemployment (Brida and Pulina, 2010). There are also differences of opinion for economic-driven tourism growth expressed in many works (see, e.g. Oh, 2005; Payne and Mervar, 2010). They presume that tourism is being developed through current economic steps connected to human capital on the rebound and this forms the basis for subsequent support of tourism activities. Dritsakis (2012) has shown more significant influence of tourism on small developing countries as opposed to developed ones. Using the VAR-based spillover index, the selected studies also demonstrate dynamic bidirectional causality as a tourism-economic relationship that is not stable over time and heavily dependent on economic events such as the Great Recession of 2007 or debt crises (Antonakakis, Dragouni, Filis, 2015). Despite current economic development, tourism is generally linked to negative influences such as overcrowding, increasing demand for goods and services, lower living standards for locals, pollution, and the devastation of environment. Society and tourism as a whole form a complex system with many induced effects.

Tourism and some related economic variables are characterized by extreme high seasonality that encompasses remarkable differences between reported levels in summer and winter months. Seasonal information is subject to strong cyclic variations within the year and should be removed from the data before analysis. However, the magnitude of seasonal fluctuations is seldom constant, together connecting the combination of economic parameters. For this reason, the standard techniques of seasonal adjustment used in relatively more stable systems, cannot be applied. In the case of variables that are non-stationary and not causally connected, the use of original time series can cause a problem especially for random variables with infinite variance. Differencing approaches help to reduce trends and seasonality. Usually the process of differencing continues until I(0) is reached, although the higher-orders lack economic interpretability. It is evident that the first differencing of the 4-quarter moving average is the same as quarterly differencing up to the constant (Robertson, 2003, p. 62). The moving averages smooth out fluctuations and short-term volatility in majority of time-series data. But traditional moving averages have the disadvantage of insinuating a lag effect or generally close processes into computations. Despite the fact that no every econometrician agrees with the differencing approach, because this process causes some loss of information in the original series, the results can be interpreted as relative to the shifts of time series.

SEM is an increasingly popular statistical method used for testing complex models with several endogenous (dependent) and exogenous (independent) variables. This popularity is also increasing in the tourism industry despite debates on the appropriateness of different fit indices, multivariate normality conditions, sample size, and various estimation methods. The advantage of SEM over other theoretically well-equipped regression approaches (Bílková, 2020) is that structural equations are able process complex models covering various real situations. This is despite fact that the requirement of sufficient reliability is seldom fulfilled in social sciences (Bohrnstedt and Carter, 1971). Modelling for unexplained variances in endogenous variables is also an advantage of structural equations. Moreover, for a model with a poor fit, it can be decided if this is due to a lack of correlations between input variables or because of the poor reliability of indicators used. SEM also allows for modelling recursive and non-recursive causal relationships. But opposite to explanatory approaches, all relational patterns in SEM must be fully established on the background theory of the problem. Studies suggest that no unified rule-of-thumb exists in the SEM modelling environment, rather the emphasis should be placed on a decision regarding each type of evidence in a particular study, taking into account the whole model and deviations from input assumptions (Nye and Drasgow, 2011; Williams and O' Boyle, 2011).

The approaches of structural modelling can be divided into i) the confirmatory factor analysis model, ii) simultaneous equations approach (also called path analysis), and iii) a full structural solution. In this study, the econometric technique of simultaneous equations is used for exclusively measurable (directly observed) variables without incorporating latent constructs because the variables do not allow their generation in a differentiated data space. For the number of specific rules, these approaches differ by identification, where necessary and sufficient conditions are often directly available. The estimation methods that can be mentioned include maximum likelihood, generalized least squares, weighted and unweighted least squares, asymptotically distribution-free criterion, and ordinary least squares. Maximum likelihood estimation with the assumption of multivariate normality is the dominant approach for SEM techniques. An alternative estimation approach of generalized least squares does not involve a multivariate normality assumption based on input data (Hayduk, 1987). But the application requirement of such alternate methods often lies in a large sample of data, so the results can be evaluated as valid. Currently, Bayesian structural equation modelling should be mentioned. Partial least squares path modelling can also be considered as a variant approach to SEM that is not based on a covariance matrix, which belongs to the family of soft-modelling techniques.

Since SEM is an only approximation to reality, the number of fit indices measures the goodness of the model hypothesized. The most common fit statistic is chi-square, based on the likelihood ratio of value testing a hypothesized model opposite to the alternative, where the covariance matrix is unconstrained (Bagozzi and Yi, 1988). But there exist many additional indices measuring the appropriateness of the model from different perspectives. Evaluation, reporting and the consequent interpretation of model fit indices are one of the most controversial issues in practice. Covering the effect size, R^2 criterion is essential to evaluate the structural model and it corresponds to a proportion of endogenous variables variance explained by the exogenous ones. But there are known cases of acceptable fit indices that account for 1% of the variance in endogenous variables (see, e.g. Tomarken and Waller, 2003). Hoyle and Panter (1995) also mention the incomplete reporting of R^2 for endogenous variables in the model. Any alternative models almost always exist for the data and the specification of alternative models is often ignored (MacCallum et al., 1993). The models are usually respecified due to relations being weaker than expected, in accordance with the model substantive meaning, and with theoretical and empirical justification (Anderson and Gerbing, 1984; Hoyle and Panter, 1995).

Literature focusing on tourism for Central and Eastern Europe lack specific causal modelling, predominantly included in a panel data analysis targeted to wide areas, without incorporating local results. We concentrate on the Czech Republic and Slovakia for differenced data. Due to the nature of this study and inductive results, satisfying both substantive (economic) and statistical significance (Gunter, Önder, Smeral, 2019), is expected.

1 DATA AND METHODS

1.1 Data used

According to Lim (2006), and Song and Witt (2000), the dependent variables most often used for tourism demand modelling are the number of arrivals, length of stay or overnights, and tourist receipts. On the other hand, independent variables consider many fundamental and derived indicators, e.g. income in the country of origin and discretionary income omitting expenditures for necessities, are the most frequent. It consists of the nominal or per capita disposable or national income and GDP or GNP as proxies for income. The studies also use income divided into wage and non-wage elements. Relative prices should be mentioned where the consumer price index and other factors often serve as proxies adjusted for differences in exchange rates between two destinations. Rather, the nominal exchange rates frequently used in studies are mistakenly perceived by tourists and do not respond to relative inflation rates. Other factors include transportation costs, promotion, direct foreign investment, capital outflows and economic indicators such as unemployment, real assets, government budget forecast, or change in income and income distributions. On the other hand, the study separating business, holiday flows and visits to friends and relatives (Turner and Witt, 2001) use explanatory variables based on destination living cost, airfare, retail sales, new car registration, GDP, trade openness, exports, imports, domestic loans, number of working days lost, and population.

Covering the time range of January 2003 to December 2019, the European Statistical Office database (Eurostat, 2019) has been used to download the information, unless otherwise stated. The scale is month or quarter for consequent use of a disaggregation approach (Rojíček et al., 2009) on neither seasonally nor calendar adjusted data. In the case of incorporating destination living cost, relative wages and salaries, and balance of payments, these are weighted by nights spent in the three most significant source countries in 2018 relative to the target one. The main sources are namely Germany, Slovakia and Poland for the Czech Republic and the Czech Republic, Poland and Germany covering Slovakia. Despite the fact, that relationships should be specified in advance for using causal modelling analysis, we consider all inputs significant in terms of tourism demand. However, the balance of payments parameter, as an example, is used only for seasonally differenced data due to the expectation of its impact on a longer scale. Rather than modelling regression connections between endogenous variables, the covariance relations are used, having a beneficial interpretation in a zero lag. The input variables considered in this study are summarized below, together with their abbreviated expressions.

Adjusted consumer prices correspond to the harmonized index of consumer price divided by Euro/ECU exchange rates in cases of national currency. The harmonized index is the overall index excluding energy and it connects the base in 2015. With wages and salaries at current prices as a part of national accounts in millions of Euros, disaggregation is used according to the wholesale and retail trade indicator. The balance of payments covers both goods and services in millions of Euros and, with a partner, the rest of the world. In this case, few-months forecasting is applied. Labour productivity index is also based on 2015 and covers real labour productivity per person. For labour productivity, disaggregation according to the industrial production indicator is used. In the case of trade openness, total import and export are outside the EU28 (extra EU) for trade. Here, disaggregation is applied for GDP with the industrial production indicator. In this study, GDP and its main components (output, expenditure and income) is the gross domestic product at market prices, current prices, and in millions of Euros. The use of two identical indicators has been tested for the interrelationships of the variables. Using the adjusted test on equality for two correlation coefficients, with the resulting statistic approximated by normal distribution, the null hypothesis is not rejected at the 1% significance level. Unemployment is expressed in thousands of persons. The data for domestic loans are collected by central banks. Here, it is converted to Euros based on averaged monthly series in the case of currency other than the national one. The consumer confidence indicator is used for balance.

Exogenous variables

DLC – destination living cost: adjusted consumer prices for weighted source countries at the ratio to the studied country;

RWS – relative wages and salaries: wages and salaries as a part of the GDP for source countries in the weighted form to the wages and salaries of the target country;

BAP – balance of payments: the balance of payments for source countries in weighted form to the studied one;

ACP – adjusted consumer prices: the harmonized index of consumer price divided by Euro/ECU exchange rates in the case of national currency;
LAP – labour productivity: real labour productivity per person as part of the quarterly national accounts;
TRO – trade openness: the sum of total import and export divided by the GDP of the target country;
HAU – harmonized unemployment: total unemployment considered;
DOL – domestic loans: the liabilities of households and non-profit institutions serving households with loans;
COC – consumer confidence: the balance of consumer confidence indicator.

Internal data for the number of arrivals and nights spent are provided by national statistical offices. They are linked to selected accommodation establishments, i.e. hotels, holiday and other short-stay accommodation, camping grounds, recreational vehicle parks and trailer parks. A forecast for arrivals is used in Slovakia. Forecasts for nights spent are used, however, for both the Czech Republic and Slovakia.

Endogenous variables
NRR – non-resident's and resident's ratio: arrivals of non-residents from the three most significant source countries to residents of the target country;
NTS – nights spent: overnights totalling three source countries and the studied one.

1.2 Methods

We consider trend and seasonality to be stochastic. The quarterly data averaged from monthly observations used as inputs cover further analyses. Such an approach allows for the monthly lag shift a more detailed process of the time series and serves to achieve an accurate prediction. Given the interpretational purposes of the demand elasticities, heteroskedasticity of input variables or potential asymmetric distribution, the log form of data is used, to which differentiation is further applied. Although the dummy variables are often used to model the remaining seasonality, the data are first differenced directly, and then for the 4-quarter moving averages, to smooth out seasonal variations. The Augmented Dickey-Fuller test reveals that the resulting series has no unit root at a 5% significance level, excepting tourism parameters that are stationary up to a significance of 0.1. In analysis, the number of observations varies, covering both differencing approaches and time series processes. The last step in treating the data is min-max normalization applied for overcoming excessively high input variances of some variables and for results interpretation. However, this adjustment modifies the model specified in a certain sense, generating certain goodness-of-fit measures, and it changes the parameter estimates and standard errors differently to using the correlation matrix (Ramlall, 2016). At min-max normalization, the fitting functions are scale-invariant with scale-free structural estimates. Any variable with a steadier distribution and minor distant observations makes a significant entrance into the analysis, which should be considered. Note that the strongly within collinear exogenous variables are rather omitted from analysis, as the modelling of covariance relations is limited. But the outputs for full extent of covariances and the one used herein do not differ in a great extent for the sample examples. Some numerical obstacles occur exceptionally when covering the time lag of selected variables.

Although the general model is more complex, the simultaneous equations system for measurable variables is used herein as a part of multivariate statistical analysis with broad applications (Bollen, 1989). For the presentation of the examined relations, we introduce the equation entry (Jöreskog, 1973; Jöreskog and Sörbom, 1979) as well as path diagrams (Keesing, 1972). Often, expressions for 1st and 2nd derivatives according to their structural parameters are necessary for the realization of numerical methods. The more general model than applied in this study and 1st derivative by using matrix differential calculus in a reduced form, are demonstrated in the Annex. It consists of the alternative derivation using a matrix trace in connection with the differential instead of the usual *vec* operator. Magnus and Neudecker (2019) mention such form in a universal sense. We use predominantly the maximum likelihood estimation for some of its advantages, e.g. it can overcome some degree of violation of the multivariate normality condition set for input data (Bollen, 1989). The number of independent elements in induced covariance matrix with some parameters fixed, make for 19 or 20 estimated parameters the approaches overidentified. Null **B** rule is sufficient for identification in our case. However, the models have correlated error terms and each equation consists of different set of regressors. To distinguish our method from those as seemingly unrelated regression, we use the structural equation methodology for its advantageous representation and perform some improvements on fit function having a direct effect on convergence. The variances of the variables are explicitly set as unknown. The R software environment (R Core Team, 2019) is used to solve the specific problem with the support of various packages: *sem* (Fox, 2017) – especially optimizerSem is used as a modified version of the current standard R optimizers, *tempdisagg* (Sax, 2020) – with special attention paid to the Chow-Lin method and *forecast* (Hyndman, 2020) – the ARIMA forecasting is targeted herein.

The goodness-of-fit statistics most often measure the difference between the observed covariance matrix and the covariance matrix implied by the model. The hypothesis $H: \mathbf{\Sigma} = \mathbf{\Sigma}(\boldsymbol{\theta})$ forms the main test in this study, approximated by chi-square distribution, opposite to the alternative, where $\mathbf{\Sigma}$ is unstructured (Bollen, 1989). The test statistic converges asymptotically to chi-square given by:

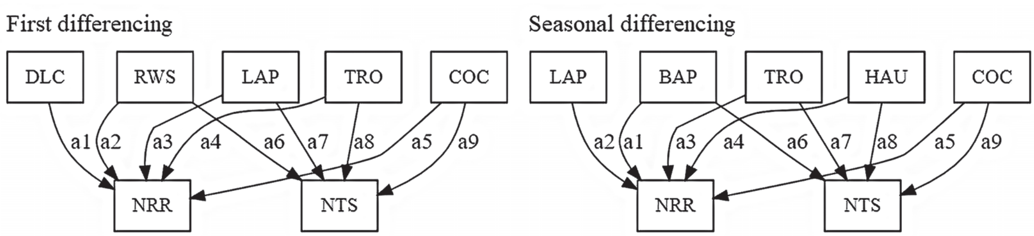
$$\chi^2 \approx (N-1) F\left(\mathbf{S}, \mathbf{\Sigma}(\boldsymbol{\theta})\right), \tag{1}$$

sensitive to a lack of multivariate normality, and particularly, by kurtosis. The simulation studies confirm that in small samples of $N < 100$, the chi-square test statistic tends to be large (Boomsma, 1983; Anderson and Gerbing, 1984). The chi-square dependencies on correlations within the model are also known. Despite this fact, we consider chi-square as the most significant and applied test overall. Although the decision that the proposed model is not wrong, a p-value greater than 0.05 is selected for an acceptable model fit. The second criterion consisted of Akaike's information criterion (AIC) derived from the chi-square estimator indicated by (1) covering a null hypothesis used for comparison of models without the usual split samples incorporation. For overall model evaluations, the Bayesian criterion (BIC) is also used. Squares of multiple correlation coefficients and t-tests of individual coefficients and covariances are included herein. We use modification indices like Lagrange-multiplier asymptotically distributed as one-df chi-square score test statistics for the fixed and constrained parameters of the structural equation model.

2 RESULTS AND DISCUSSION

The model structures for the Czech Republic and Slovakia, separate in both first and seasonally differenced data, are graphically represented below (Figure 1). In the following, the results are with zero lags deep

Figure 1 Path diagrams



Source: Authors

interpreted. Negative values of BIC in such points demonstrate an exquisite fit for all models. The explicitly defined variances set as unknown, are not introduced in the following text, together with the modelled covariances demonstrated only in equational format.

In both countries, the proper model for first differenced data is achieved after a few modifications of the initial idea for adopting the additional covariances (cov). The only variable excluded by the modified version is DOL, due to the great degree of collinearity. The ACP parameter is omitted directly before the analysis. Expressed by equations, the first differenced system is as follows:

$$\mathrm{NRR} = \mathrm{a1\ DLC} + \mathrm{a2\ RWS} + \mathrm{a3\ LAP} + \mathrm{a4\ TRO} + \mathrm{a5\ COC}\,,$$

$$\mathrm{NTS} = \mathrm{a6\ RWS} + \mathrm{a7\ LAP} + \mathrm{a8\ TRO} + \mathrm{a9\ COC}\,,$$

Czech Republic

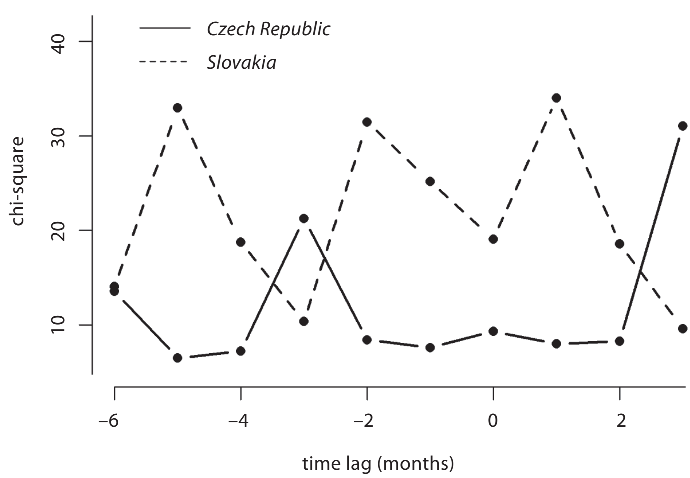
$$\mathrm{cov}(\mathrm{DLC},\ \mathrm{RWS}) = \mathrm{c1},\ \mathrm{cov}(\mathrm{RWS},\ \mathrm{LAP}) = \mathrm{c2},\ \mathrm{cov}(\mathrm{LAP},\ \mathrm{TRO}) = \mathrm{c3},\ \mathrm{cov}(\mathrm{NRR},\ \mathrm{NTS}) = \mathrm{c4}\,,$$

Slovakia

$$\mathrm{cov}(\mathrm{DLC},\ \mathrm{LAP}) = \mathrm{c1},\ \mathrm{cov}(\mathrm{DLC},\ \mathrm{COC}) = \mathrm{c2},\ \mathrm{cov}(\mathrm{RWS},\ \mathrm{TRO}) = \mathrm{c3},\ \mathrm{cov}(\mathrm{NRR},\ \mathrm{NTS}) = \mathrm{c4}.$$

Covering Figure 2, the process of time lag for economic parameters are stated in some sense contrary to the spectral time-series data processing, as negative lag demonstrates delayed endogenous tourism variables. Although the maximum likelihood fit function is used for problem solving and has indisputable benefits, the generalized least squares approach is accommodated in the case the numerical algorithm fails. Assuming a true null hypothesis, multivariate normality of data for a maximum likelihood estimation and a sufficient sample size, both fit functions yield an approximate chi-square by multiplying them by (N – 1) and the discrepancy function (Loehlin, 2004, p. 54). No evident trend in the data is observed covering the Czech Republic and Slovakia. But generally, for both types of differencing, the relational pattern remains relatively constant to some degree of time shift. This fact confirms the suitability of selecting a zero lag for interpretational purposes.

Figure 2 Processes for first differences



Source: Authors

For the Czech Republic, the chi-square statistic value 10.24 and corresponding p-value 0.249 supports the model for goodness-of-fit. AIC criterion gains the approximate value 50.24, where about 35.62% variability of NRR, as well as 27.87% variability of NTS, are explained by the model. These are relatively small proportions. In the case of Slovakia, the chi-square statistic value 14.46 and corresponding p-value 0.071 supports the model for goodness-of-fit. AIC criterion gains the approximate value 54.46, where about 70.57% variability of NRR, as well as 76.38% variability of NTS, are explained by the model. Compared to the results of the Czech Republic, these values are significantly higher.

Below, the coefficients are interpreted for p-value < 0.1 covering Table 1. In the Czech Republic for first differencing of data, both LAP and TRO have a significant positive influence on NRR. On the other hand, NTS is most influenced by TRO negatively, then positively by COC, and again negatively by RWS. So, a higher degree of workload and open trade decrease the number of residents. The negative relation of TRO and RWS to NTS can be partially explained by the high input negative correlation of the first differenced NRR to NTS. COC positively influences NTS, which is expected. In Slovakia, the situation is reversed due to the strong positive correlation of NRR to NTS. Here, RWS has an especially positive influence on NRR. TRO has a negative influence on non-residents, while both LAP and COC have a positive influence. RWS, then LAP and COC, positively relate to NTS, here caused by non-residents. TRO negatively relates NTS. This is because at increasing residents, NTS falls with regards to the input data. An RWS, preferring source countries, provides non-residents to this territory. In the case of open trade, Slovaks prefer their own country.

In both countries, the proper model for seasonally differenced data after adopting the necessary covariances, is expressed in equational form as follows:

$$\mathrm{NRR} = \mathrm{a1\ BAP} + \mathrm{a2\ LAP} + \mathrm{a3\ TRO} + \mathrm{a4\ HAU} + \mathrm{a5\ COC},$$

$$\mathrm{NTS} = \mathrm{a6\ BAP} + \mathrm{a7\ TRO} + \mathrm{a8\ HAU} + \mathrm{a9\ COC},$$

Czech Republic

$$\mathrm{cov}(\mathrm{BAP},\ \mathrm{LAP}) = \mathrm{c1},\ \mathrm{cov}(\mathrm{LAP},\ \mathrm{HAU}) = \mathrm{c2},\ \mathrm{cov}(\mathrm{TRO},\ \mathrm{COC}) = \mathrm{c3},$$

Slovakia

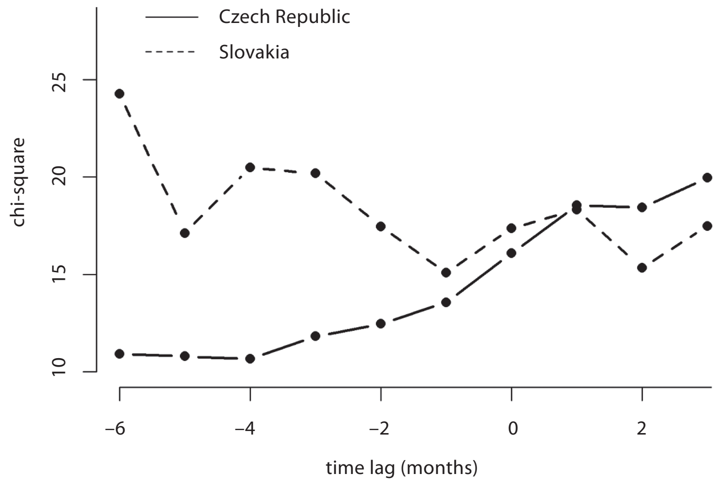
$$\mathrm{cov}(\mathrm{LAP},\ \mathrm{TRO}) = \mathrm{c1},\ \mathrm{cov}(\mathrm{LAP},\ \mathrm{COC}) = \mathrm{c2},\ \mathrm{cov}(\mathrm{BAP},\ \mathrm{LAP}) = \mathrm{c3}.$$

Table 1 Coefficients for first differenced data

Coeff	Czech Republic				Slovakia			
	Estimate	StdError	*t*-statistic	*p*-value	Estimate	StdError	*t*-statistic	*p*-value
a1	−0 .0438	0.0895	−0.489	6.25e-01	−0.0019	0.0573	−0.032	9.74e-01
a2	0.2378	0.1893	1.256	2.09e-01	0.6910	0.0755	9.153	5.54e-20
a3	0.5694	0.1344	4.235	2.29e-05	0.1672	0.0587	2.848	4.40e-03
a4	0.6241	0.1885	3.310	9.33e-04	−0.3786	0.0817	−4.632	3.63e-06
a5	−0.3186	0.2600	−1.226	2.20e-01	0.2256	0.1102	2.048	4.06e-02
a6	−0.3238	0.1915	−1.691	9.08e-02	0.8224	0.0916	8.975	2.83e-19
a7	−0.1752	0.1412	−1.241	2.15e-01	0.4321	0.0705	6.131	8.73e-10
a8	−0.7788	0.1996	−3.902	9.56e-05	−0.5877	0.0992	−5.923	3.16e-09
a9	0.5294	0.2756	1.921	5.47e-02	0.4331	0.1318	3.287	1.01e-03
c1	0.0207	0.0044	4.661	3.15e-06	0.0101	0.0051	2.001	4.54e-02
c2	0.0241	0.0060	3.989	6.65e-05	0.0062	0.0028	2.257	2.40e-02
c3	−0.0163	0.0059	−2.781	5.42e-03	−0.0119	0.0052	−2.305	2.12e-02
c4	−0.0697	0.0126	−5.553	2.82e-08	0.0146	0.0028	5.126	2.96e-07

Source: Authors

Figure 3 Processes for seasonal differences



Source: Authors

The process of time lag for economic parameters is stated in Figure 3. Compared to first differenced data, the range of statistic values is relatively lower, and a growing linear trend is partially revealed in the Czech Republic, excepting tourism lags.

Covering the Czech Republic, the chi-square statistic value 15.27 and corresponding *p*-value 0.084 supports the model for goodness-of-fit. AIC criterion gains the approximate value 53.27, where a 39.06% variability of NRR, as well as a 15.26% variability of NTS, is explained by the model. The value considering NTS is relatively low. In the case of Slovakia, the chi-square statistic value 14.58 and corresponding *p*-value 0.103 supports the model for goodness-of-fit. AIC criterion gains the approximate value 52.58, where a 41.49% variability of NRR, as well as a 34.16% variability of NTS, is explained by the model. Compared to the results of the Czech Republic, these values are significantly higher.

Table 2 Coefficients for seasonally differenced data

Coeff	Czech Republic				Slovakia			
	Estimate	StdError	*t*-statistic	*p*-value	Estimate	StdError	*t*-statistic	*p*-value
a1	0.2486	0.1370	1.815	6.96e-02	−0.0347	0.1032	−0.337	7.36e-01
a2	0.3806	0.1127	3.377	7.33e-04	0.1006	0.1462	0.688	4.92e-01
a3	−0.3085	0.1212	−2.546	1.09e-02	0.3336	0.1107	3.015	2.57e-03
a4	0.2467	0.1201	2.053	4.00e-02	−0.2720	0.0914	−2.976	2.92e-03
a5	0.3270	0.1491	2.194	2.83e-02	0.3908	0.1281	3.051	2.28e-03
a6	0.1134	0.1470	0.771	4.41e-01	0.1143	0.1075	1.063	2.88e-01
a7	−0.0544	0.1442	−0.377	7.06e-01	0.2167	0.0967	2.241	2.50e-02
a8	−0.3317	0.1329	−2.497	1.25e-02	−0.5088	0.1011	−5.031	4.87e-07
a9	−0.3692	0.1774	−2.081	3.75e-02	−0.1019	0.1219	−0.836	4.03e-01
c1	0.0180	0.0058	3.131	1.74e-03	0.0212	0.0051	4.118	3.82e-05
c2	−0.0165	0.0060	−2.735	6.23e-03	0.0129	0.0036	3.584	3.39e-04
c3	−0.0065	0.0039	−1.658	9.72e-02	0.0088	0.0035	2.522	1.17e-02

Source: Authors

In the Czech Republic, all exogenous variables are significant for NRR, where the lowest p-value gains LAP. All BAP, LAP, HAU and COC are positively related to non-residents covering one exception of TRO. Both HAU and COC have a significant negative influence on NTS. The relations are different to first differenced data due to long-lasting processes and the later achievement of economic equilibrium in the data. HAU has a negative influence, especially for residents. The extra behaviour of the TRO and COC parameters is probably due to their relation, although not so significant. Covering Slovakia, TRO and COC are both significantly and positively related to NRR. But the HAU influence is negative. HAU especially relates negatively, and TRO positively, to NTS. Such a behavioural pattern is expected.

CONCLUSION

Tourism is a fundamental part of the global economy depending heavily on human capital. Applying the SEM approach of simultaneous equations to Central European countries for first and seasonally differenced time series data has demonstrated its appropriateness. Despite a fact, the number of scientists argues the economic theory cannot handle differences due to long-run relationships, and the equilibrium stages theory gravitates toward, we interpret the results as shifts in input data. The chi-square statistics for all the explained models are not significant at the 5%, even accompanied by other statistics. It is important to note, the identical models for the Czech Republic and Slovakia are selected, due to their relatively close history and specific economies. Parameters persisting the first and seasonal differencing are perceived especially important. Although a deeper examination is incorporated herein, we summarize the most significant outputs below. The results can capture members of destination management at the national and international levels.

Covering a short-term measure of changes in the sense of first differences, labour productivity and trade openness are the most important parameters in the Czech Republic, while relative wages and salaries parameter is the most significant in Slovakia. An assumption of the importance of relative wages and salaries in both countries is not confirmed. The workload of residents negatively influences total nights spent caused by non-residents in the Czech Republic stay shorter. Because trade openness enhances the number of non-residents relative to residents apparently, this also decreases the number of nights spent. In the Czech Republic, the workload and probably higher level of the wages for selected groups avoid travelling to a great extent, or departures of Czechs go abroad. As tourism is a part of the global economy, the increased import and export have on non-residents a positive influence. In Slovakia, opposite relations in many cases, are observed. Trade openness negatively influences non-residents as Slovaks prefer their own territory and reveal shorter stays compared to non-residents. From this reason, in a short horizon of changes, the import and export decrease nights spent. The higher degree of workload also decreases residents. But in Slovakia, the main factor is relative wages and salaries increasing non-residents which consequently enhances nights spent. Contrarywise, in the Czech Republic, the relative wages and salaries has significant influence only for nights spent. The negative relation is an expression of the reality that increased wage level in source countries should raise the activity of non-residents, contrary spending less time. Both countries separate as the Czech Republic is more concentrated on the global economy and its consequences. Slovaks are more directed to their own country in the short horizon. On the other hand, consumer confidence positively, and trade openness negatively, relate nights spent in both countries. So, confidence and corresponding safety are perceived positively, connected to stays, while the global economy has the effect reversed.

For the Czech Republic and long seasonal horizon, again one of the most significant factors is labour productivity. Between others, harmonized unemployment negatively influences residents, while decreases nights spent. In the case of a first differencing, the trade openness has a positive influence on non-residents, but in a long horizon of mutual changes, the role adopts residents. The consumer confidence relation to nights spent is strange and can be caused by their primary mutual relations. Covering Slovakia, all pattern is expected. Despite for a range of the short time changes, trade openness negatively influences non-residents, moreover here, the relationship is reversed in connection to increased nights spent. For a long horizon of changes, global economy expressed by import and export is more pronounced. While labour productivity persists in the Czech Republic as a significant factor increasing non-residents, trade openness alters its role as supports residents. The influence of import and export in Slovakia is proven opposite completely, as the global economy rather positively relates non-residents on a long horizon. Also, note the significant role of harmonized unemployment differing its influence between both countries for non-residents and residents, as negatively influences nights spent generally. Specific visitors to countries studied are negatively perceived by such a parameter, eliminating seasonal fluctuations. Consumer confidence positively relates non-residents for both territories. The relations included in both short, as well as a long horizon of changes, are especially labour productivity and corresponding wages influence to non-residents in the Czech Republic. Mutual comparison of both countries reveals predominantly different trade openness behaviour as a factor of the global economy in first and seasonally differenced data. Such results can precise the planning capacity of accommodation establishments, the number of bed places, hospitality, and other industries.

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ANNEX

The simultaneous equations system has the general expression:

$$y = \mathbf{B}\, y + \boldsymbol{\Gamma}\, x + \zeta, \tag{a}$$

where both $\mathbf{B}$ $(p \times p)$, $\boldsymbol{\Gamma}$ $(p \times q)$ are matrices of coefficients with y $(p \times 1)$, x $(q \times 1)$ and ζ $(p \times 1)$ random vectors. Vector y marks endogenous variables, x is the vector of exogenous variables and ζ corresponds to the vector of random errors (Timm, 2002). Here, $E(x) = E(\zeta) = 0$, and thus $E(y) = 0$, variables are centred, and x with ζ are moreover uncorrelated. $\mathbf{\Phi}$ is the covariance matrix of x and $\mathbf{\Psi}$ is the covariance matrix of ζ. Furthermore, we consider $x \sim N_q(0, \mathbf{\Phi})$, $\zeta \sim N_p(0, \mathbf{\Psi})$. If we expect the matrix $(\mathbf{I} - \mathbf{B})$ non-singular, then the model can be written in the form $y = (\mathbf{I} - \mathbf{B})^{-1}\mathbf{\Gamma}x + (\mathbf{I} - \mathbf{B})^{-1}\zeta$.

Covering $\mathbf{B} = \mathbf{0}$, model (a) can be perceived as one of the specific forms of multivariate regression. If $\mathbf{B}$ is lower triangular matrix and the errors are not correlated, then the model is recursive.

The population covariance matrix of vector $(y, x)'$ can be written $\mathbf{\Sigma}$ and its expression in structural parameters $\boldsymbol{\theta} = (\mathbf{B}, \mathbf{\Gamma}, \mathbf{\Phi}, \mathbf{\Psi})$ is as follows:

$$\mathbf{\Sigma}(\boldsymbol{\theta}) = \begin{bmatrix} (\mathbf{I}-\mathbf{B})^{-1}(\mathbf{\Gamma\Phi\Gamma}'+\mathbf{\Psi})(\mathbf{I}-\mathbf{B})^{-1'} & (\mathbf{I}-\mathbf{B})^{-1}\mathbf{\Gamma\Phi} \\ \mathbf{\Phi\Gamma}'(\mathbf{I}-\mathbf{B})^{-1'} & \mathbf{\Phi} \end{bmatrix}. \tag{b}$$

The term for model identification is a key in structural equations, although the *Error message* is often incorporated in various program environments. According to Bollen (1989), the parameter is identified, if it can be expressed using elements of matrix $\mathbf{\Sigma}$. The model is identified if all elements of $\boldsymbol{\theta}$ can be expressed in this way. The problem of identification is solved in special cases (Skrondal and Rabe-Hesketh, 2004). The matrix $\mathbf{\Sigma}$ often is not available as approximated by sample covariance matrix $\mathbf{S}$.

The symmetric matrix in (b) has the order $(p + q)$. The number of its independent elements is thus $v = \frac{p+q}{2}(p+q+1)$. We concentrate our attention only on the fundamental equality solution $\mathbf{\Sigma} = \mathbf{\Sigma}(\boldsymbol{\theta})$ for the unknown $\boldsymbol{\theta}$ as the number of elements of $\boldsymbol{\theta}$ must be $\leq v$.

Two cases for parameter identification embracing special conditions are:

1) For $\mathbf{B} = \mathbf{0}$ holds $\boldsymbol{\theta} = (\mathbf{\Gamma}, \mathbf{\Phi}, \mathbf{\Psi})$. If $\mathbf{\Sigma} = \begin{bmatrix} \mathbf{\Sigma}_{yy} & \mathbf{\Sigma}_{yx} \\ \mathbf{\Sigma}_{xy} & \mathbf{\Sigma}_{xx} \end{bmatrix}$, then $\mathbf{\Gamma}' = \mathbf{\Sigma}_{xx}^{-1}\mathbf{\Sigma}_{xy}; \mathbf{\Gamma\Phi\Gamma}' + \mathbf{\Psi} = \mathbf{\Sigma}_{yy}$, from where $\mathbf{\Psi} = \mathbf{\Sigma}_{yy} - \mathbf{\Sigma}_{yx}\mathbf{\Sigma}_{xx}^{-1}\mathbf{\Sigma}_{xy}$.
2) If the model is recursive, then identification is related to an algebraic operation, i.e. elimination.

In the following, the model is expected to be identified. We have a joint probability density $f(z, \boldsymbol{\theta})$ of the random vector $z = (z_1, z_2, ..., z_n)$ dependent on the parameters $\boldsymbol{\theta}$. The scalar fit functions are constructed as $F(\mathbf{S}, \mathbf{\Sigma}(\boldsymbol{\theta})) \geq \mathbf{0}$, smooth enough, for which $F(\mathbf{S}, \mathbf{\Sigma}(\boldsymbol{\theta})) = 0 \Leftrightarrow \mathbf{\Sigma}(\boldsymbol{\theta}) = \mathbf{S}$. The sample covariance matrix is $\mathbf{S} = \frac{1}{N-1}\sum_{i=1}^{N}(z_i - \bar{z})(z_i - \bar{z})'$ with the number of observations N. The point $\boldsymbol{\theta}_0$, where the minimum of function F in variable $\boldsymbol{\theta}$ occurs, corresponds to the searched estimate of the structural parameters. We demonstrate the two estimates most often used. The first one is derived from maximum likelihood theory, the second is based on weighted least squares:

1) $F_{ML} = \ln|\mathbf{\Sigma}(\boldsymbol{\theta})| + tr(\mathbf{S\Sigma}^{-1}(\boldsymbol{\theta})) - \ln|\mathbf{S}| - (p + q)$
2) $F_{WLS} = \frac{1}{2}tr[\mathbf{W}^{-1}(\mathbf{S} - \mathbf{\Sigma}(\boldsymbol{\theta})]^2 = \frac{1}{2}\|\mathbf{W}^{-1}(\mathbf{S} - \mathbf{\Sigma}(\boldsymbol{\theta}))\|^2$,

where $\|\mathbf{M}\| = (tr(\mathbf{M}'\mathbf{M}))^{\frac{1}{2}}$ denotes the norm of matrix $\mathbf{M}$, and $\mathbf{W}$ is a weight matrix. Specifically, in case of $\mathbf{W}^{-1} = \mathbf{S}^{-1}$, the estimation method corresponds to generalized least squares, and in the case of $\mathbf{W}^{-1} = \mathbf{I}$, it is the standard method of least squares.

We indicate the solution of first estimation method F_{ML} under the assumption that vector $z = (y, x)'$ can be described by a multivariate normal distribution $\mathrm{N}(0, \mathbf{\Sigma})$. Stationary equations for searching the extrema of fit functions are (excepting special cases) nonlinear, and finding a solution is relatively difficult. There are numerical methods available in current program environments covering various optimization routines. Different gradient approaches are also worth mentioning. The realization of numerical methods in most cases requires knowing the expression for 1st and 2nd derivatives according to their structural parameters. We indicate the computations of the 1st derivative.

To find the function F_{ML} minimum, the following formula is used:

$$F_{ML} = \ln|\boldsymbol{\Sigma}(\boldsymbol{\theta})| + tr(\mathbf{S}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})). \tag{c}$$

Formula (a) is linear, but the induced covariance matrix $\boldsymbol{\Sigma}(\boldsymbol{\theta})$ given by (b) is not a linear function of the parameters. Expression (c) is a scalar function of matrix variables. As introduced below, the scalar property can be realized by matrix trace. For the computation derivatives of the 1st and 2nd order on F_{ML}, using the results of Jöreskog (1973) or Magnus and Neudecker (2019) enables us to work with its differentials. The extrema type is decided by the Hesse matrix, consisting of partial derivatives of the 2nd order for F_{ML}.

In this study, we for F_{ML} execute the 1st partial derivative which is fundamental for finding the minimum (c). The differential is used instead of the *vec* operator and Hadamard product as an alternative. We use:

$$dF_{ML}\left(\boldsymbol{\Sigma}(\boldsymbol{\theta})\right) = tr\left(\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})d\boldsymbol{\Sigma}(\boldsymbol{\theta})\right) - tr(\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\left(d\boldsymbol{\Sigma}(\boldsymbol{\theta})\right)\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\mathbf{S}) = tr\left[\boldsymbol{\Sigma}^{-1}(\boldsymbol{\Sigma}-\mathbf{S})\boldsymbol{\Sigma}^{-1}d\boldsymbol{\Sigma}\right].$$

The matrix $\boldsymbol{\Sigma}^{-1}(\boldsymbol{\Sigma} - \mathbf{S})\boldsymbol{\Sigma}^{-1} = \boldsymbol{\Omega}(\boldsymbol{\theta})$ is implemented and divided into blocks $\boldsymbol{\Omega} = \begin{bmatrix} \boldsymbol{\Omega}_{yy} & \boldsymbol{\Omega}_{yx} \\ \boldsymbol{\Omega}_{xy} & \boldsymbol{\Omega}_{xx} \end{bmatrix}$ of the same type as matrix $\boldsymbol{\Sigma}$.

The computation blocks of matrix $\boldsymbol{\Omega}$ using $\boldsymbol{\Sigma}$ is executed using the Schur complement. We get:

$$dF_{ML}\left(\boldsymbol{\Sigma}(\boldsymbol{\theta})\right) = tr\left(\boldsymbol{\Omega}_{yy}d\boldsymbol{\Sigma}_{yy}\right) + tr\left(\boldsymbol{\Omega}_{yx}d\boldsymbol{\Sigma}_{xy}\right) + tr\left(\boldsymbol{\Omega}_{xy}d\boldsymbol{\Sigma}_{yx}\right) + tr\left(\boldsymbol{\Omega}_{xx}d\boldsymbol{\Sigma}_{xx}\right).$$

The following demonstrates computation of individual elements. If we introduce a symmetric matrix $\mathbf{A} = \boldsymbol{\Gamma\Phi\Gamma}' + \boldsymbol{\Psi}$, then:

$$\begin{aligned}
&tr\left(\boldsymbol{\Omega}_{yy}d\boldsymbol{\Sigma}_{yy}\right) = tr\left\{\boldsymbol{\Omega}_{yy}d\left[(\mathbf{I}-\mathbf{B})^{-1}\mathbf{A}(\mathbf{I}-\mathbf{B})^{-1'}\right]\right\} = 2tr\left\{\boldsymbol{\Omega}_{yy}d(\mathbf{I}-\mathbf{B})^{-1}\mathbf{A}(\mathbf{I}-\mathbf{B})^{-1'}\right\} \\
&+2tr\left\{\boldsymbol{\Omega}_{yy}(\mathbf{I}-\mathbf{B})^{-1}d\boldsymbol{\Gamma\Phi\Gamma}'(\mathbf{I}-\mathbf{B})^{-1'}\right\} + tr\left\{\boldsymbol{\Omega}_{yy}(\mathbf{I}-\mathbf{B})^{-1}\boldsymbol{\Gamma}d\boldsymbol{\Phi\Gamma}'(\mathbf{I}-\mathbf{B})^{-1'}\right\} \\
&+tr\left\{\boldsymbol{\Omega}_{yy}(\mathbf{I}-\mathbf{B})^{-1}\mathrm{d}\boldsymbol{\Psi}(\mathbf{I}-\mathbf{B})^{-1'}\right\} = 2tr\left\{(\mathbf{I}-\mathbf{B})^{-1}\mathbf{A}(\mathbf{I}-\mathbf{B})^{-1'}\boldsymbol{\Omega}_{yy}(\mathbf{I}-\mathbf{B})^{-1}d\mathbf{B}\right\} \\
&+2tr\left\{\boldsymbol{\Phi\Gamma}'(\mathbf{I}-\mathbf{B})^{-1'}\boldsymbol{\Omega}_{yy}(\mathbf{I}-\mathbf{B})^{-1}d\boldsymbol{\Gamma}\right\} + tr\left\{\boldsymbol{\Gamma}'(\mathbf{I}-\mathbf{B})^{-1'}\boldsymbol{\Omega}_{yy}(\mathbf{I}-\mathbf{B})^{-1}\boldsymbol{\Gamma}d\boldsymbol{\Phi}\right\} \\
&+tr\left\{(\mathbf{I}-\mathbf{B})^{-1'}\boldsymbol{\Omega}_{yy}(\mathbf{I}-\mathbf{B})^{-1}d\boldsymbol{\Psi}\right\}.
\end{aligned}$$

$$\begin{aligned}
&tr\left(\boldsymbol{\Omega}_{xy}d\boldsymbol{\Sigma}_{yx}\right) = tr\left\{\boldsymbol{\Omega}_{xy}\left[(\mathbf{I}-\mathbf{B})^{-1}d\mathbf{B}(\mathbf{I}-\mathbf{B})^{-1}\boldsymbol{\Gamma\Phi} + (\mathbf{I}-\mathbf{B})^{-1}d\boldsymbol{\Gamma\Phi} + (\mathbf{I}-\mathbf{B})^{-1}\boldsymbol{\Gamma}d\boldsymbol{\Phi}\right]\right\} \\
&= tr\left\{(\mathbf{I}-\mathbf{B})^{-1}\boldsymbol{\Gamma\Phi\Omega}_{xy}(\mathbf{I}-\mathbf{B})^{-1}d\mathbf{B}\right\} + tr\left\{\boldsymbol{\Phi\Omega}_{xy}(\mathbf{I}-\mathbf{B})^{-1}d\boldsymbol{\Gamma}\right\} \\
&+tr\left\{\boldsymbol{\Omega}_{xy}(\mathbf{I}-\mathbf{B})^{-1}\boldsymbol{\Gamma}d\boldsymbol{\Phi}\right\}.
\end{aligned}$$

From the property of trace, we know $tr\left\{\boldsymbol{\Omega}_{yx}d\boldsymbol{\Sigma}_{xy}\right\} = tr\left\{\boldsymbol{\Omega}_{xy}d\boldsymbol{\Sigma}_{yx}\right\}$ and $tr\left(\boldsymbol{\Omega}_{xx}d\boldsymbol{\Sigma}_{xx}\right) = tr\left(\boldsymbol{\Omega}_{xx}d\boldsymbol{\Phi}\right)$. Thus $dF_{ML}\left(\Sigma(\boldsymbol{\theta})\right)$ can be expressed in partial differentials of the structural parameters:

$$dF_{ML}\left(\boldsymbol{\Sigma}\left(\boldsymbol{\theta}\right)\right)=tr\left\{2\left(\mathbf{I}-\mathbf{B}\right)^{-1}\left[\mathbf{A}\left(\mathbf{I}-\mathbf{B}\right)^{-1'}\boldsymbol{\Omega}_{yy}+\boldsymbol{\Gamma\Phi\Omega}_{xy}\right]\left(\mathbf{I}-\mathbf{B}\right)^{-1}d\mathbf{B}\right\}$$
$$+tr\left\{2\boldsymbol{\Phi}\left[\boldsymbol{\Gamma}'\left(\mathbf{I}-\mathbf{B}\right)^{-1'}\boldsymbol{\Omega}_{yy}+\boldsymbol{\Omega}_{xy}\right]\left(\mathbf{I}-\mathbf{B}\right)^{-1}d\boldsymbol{\Gamma}\right\}+tr\left\{\left(\mathbf{I}-\mathbf{B}\right)^{-1'}\boldsymbol{\Omega}_{yy}\left(\mathbf{I}-\mathbf{B}\right)^{-1}d\boldsymbol{\Psi}\right\}$$
$$+tr\left\{\left[\left(\boldsymbol{\Gamma}'\left(\mathbf{I}-\mathbf{B}\right)^{-1'}\boldsymbol{\Omega}_{yy}\left(\mathbf{I}-\mathbf{B}\right)^{-1}+2\boldsymbol{\Omega}_{xy}\left(\mathbf{I}-\mathbf{B}\right)^{-1}\right)\boldsymbol{\Gamma}+\boldsymbol{\Omega}_{xx}\right]d\boldsymbol{\Phi}\right\}.$$

We do not take into consideration that matrices **Σ, Φ** are symmetric and **Ψ** is moreover diagonal in some cases, which can simplify the computations. The right side of the resulting formulas has the shape $tr(\mathbf{G}_i d\boldsymbol{\theta}_i)$. Then, by the work of Magnus and Neudecker (2019), the matrices $(vec\mathbf{G}_i')'$ are partial derivatives of F_{ML} according to the structural parameters.

Multivariate Analysis of Fertility: an Application of the Generalized Poisson Regression Model

Adelaide Agyeman [1] | *CSIR-Science and Technology Policy Research Institute, Accra, Ghana*

Abstract

Total fertility rate (TFR) is a standard measure commonly used to estimate fertility levels and trends. However, TFR is a period measure and does not offer reasons for observed variations in fertility rates and trends. Using data from the 2017 Ghana Maternal Health Survey (GMHS), this study examines current fertility levels and trends of ever-married women and employs a generalized Poisson regression (GPR) model to analyze the determinants of fertility. Findings suggest that the current fertility level of 5.4 for ever-married women is high. The results also reveal that age at first marriage, educational level, household wealth, area of residence, use of contraceptives; and ownership and use of a bank account are significant determinants of total fertility ($p<0.05$) and are thus factors that affect the fertility levels of women. The study concludes that the GPR analysis provides a clearer picture of the nature and determinants of fertility compared to the standard TFR analysis.

Keywords	***JEL code***
Total fertility, generalized Poisson regression model, determinants, sub-Saharan Africa	*C52, R2*

INTRODUCTION

Population growth is a key evolving global challenge (Glenn et al., 2014) and current trends have sparked debates on its possible adverse effect on the achievement of the United Nations' Sustainable Development Goals (SDGs) in especially developing countries (Jatana and Currie, 2020). According to a 2017 report by United Nations Development Programme (UNDP) and United Nations Research Institute for Social Development (UNRISD), developing countries which are experiencing rapid population growth are likely to face the challenge of providing quality social services, including health and education, as well as decent employment opportunities (Trends, 2017). Ghana's current 2.2% population growth rate is much higher than the world rate of 1.1% and is thus a disturbing trend (World Bank, 2019).

In most settings and in the long term, total fertility rate (TFR) which represents the average number of children per woman is one of the key determinants of the population dynamics and growth and can be

[1] CSIR-Science and Technology Policy Research Institute, P.O.Box, CT. 519 Cantonments, Accra, Ghana. E-mail: nesiagyeman@yahoo.com, phone: (+233)302210773856.

an excellent indicator of the future population growth or decline for a country (UN DESA, 2019). Recent studies, report of declining TFR trends worldwide with statistics indicating that since 1950 the global fertility rate has halved to about 2.4 (Murray et al., 2018). In spite of declining fertility rates globally, sub-Sahara Africa remains the region with the highest fertility at 4.6 children per woman (UN DESA, 2020). Although, TFR is a simple and comparable summary measure used extensively to acquire information on the current and total fertility trends and dynamics and track fertility rates (Pol and Thomas, 2002), it can hardly offer a holistic explanation for the observed changes in fertility rates and trends.

The theory of fertility and empirical evidence indicate that fertility levels and trends depend largely on demographic, socio-economic and cultural factors (Becker and Lewis, 1973; Wang and Famoye, 1997; Caudill and Mixon, 1995; Bongaarts et al., 1984). The key socio-economic and demographic characteristics, that have been used to explain the observed changes in fertility rates and trends include, age at first marriage, education, income or wealth, region, area of residence, contraception, marital-status and religion (Shapiro and Gebreselassie, 2013; Bijlsma and Wilson, 2017; Pandey and Kaur, 2015; Schoumaker, 2019). Empirical findings have revealed that, lack of educational opportunities or low levels of education (Martin, 1995), relatively low levels of contraceptive use (Bongaarts, 2017; Gyimah et al., 2012; Ekane, 2013; Wang et al., 2017; UN DESA, 2020), high levels of poverty and insecurity (Mbacke, 2017; Mansanja et al., 2016), early average age for marriage (Clifton and Frost, 2011; Garenne, 2004; Head et al., 2014) and residing in a rural area (Kulu, 2013; Ekane, 2013; Lerch, 2019) are key factors contributing significantly to the high levels of fertility in sub-Saharan Africa.

In several empirical studies on female fertility, the number of children ever born (CEB) to women in their reproductive years is modeled as a function of other social and economic variables (Wang and Famoye, 1997; Melkersson and Rooth, 2000). CEB is essentially a count discrete random variable and the standard Poisson regression model described in the context of generalized linear models by McCullagh and Nelder (1989) has been widely used to model such data (Winkelmann and Zimmermann, 1994). A key assumption of the standard Poisson regression model states that the variance and the mean should be equal (equi-dispersion; Cameron and Trivedi, 1998). However, it is well-known that count data often exhibit over-dispersion (i.e., the variance is greater than its mean) or in less common cases, under-dispersion (i.e., the variance is smaller than its mean). In situations where the equi-dispersion assumption of the standard Poisson regression model is violated, the parameter estimates can still be consistent but inferences based on the estimated standard errors will be incorrect and misleading (Winkelmann and Zimmermann, 1995; Harris and Yang, 2012; Famoye et al., 2004). Alternatively, the generalized Poisson regression (GPR) model has shown statistical advantages over the standard Poisson regression model in terms of its ability in modeling either over-dispersed or under-dispersed count data sets. The GPR model also provides a flexible approach for analyzing count random variables as a function of other variables (Singh et al., 2000). Wang and Famoye (1997), and Wilkermann and Zimmermann (1994) modeled household fertility data using the generalized Poisson regression model and found out that the GPR model yielded more efficient estimates and provided a better fit to their household fertility data.

To develop a clearer understanding of the underlying factors that affect total fertility of women, it is necessary to examine the socio-economic and demographic factors that significantly influence fertility levels and trends using versatile multivariate statistical methods. The objectives of this study were to analyze current fertility levels and trends of ever-married women and assess the key socio-economic and demographic characteristics influencing household fertility using the generalized Poisson regression model.

1 MATERIALS AND METHODS

1.1 Data

In this study we utilized data from the 2017 Ghana Maternal Health Survey (GMHS), a nationally representative survey in which 26 324 households were interviewed. A two-stage stratified probability-sampling method was used in the GMHS to select respondents that covered the then ten administrative regions of Ghana (Western, Central, Greater Accra, Volta, Eastern, Ashanti, Brong Ahafo, Northern, Upper East, and Upper West). Out of the total number of households surveyed under the GMHS, interviews were successfully completed with 25 062 women aged between 15 and 49 years. This study, however, purposively selected 17 126 ever-married women (married, living together, separated, divorced and widowed) for the analysis because of the use of "age at first marriage" as an explanatory variable.

1.2 Variables

The dependent variable for this study is a count variable denoting the number of children ever born (CEB) to ever married woman between the ages of (15–49) and it takes on non-negative integer values (Table 1). The mean number of children ever born alive to women in that age group 15–49 was calculated as:

$$\mathrm{CEB} = \sum jP_j, \tag{1}$$

where, j is the number of children P_j is the proportion of ever-married women age 15–49 who have given birth to a total of j children.

The explanatory variables are also presented in Table 1.

Table 1 Variable definitions

Variable	Description
Total children ever born (CEB)	Total number of children to female respondents between the age of (15–49) years
Age	Age of female respondents (15–49)
Age squared	Age squared of female respondents
Age at first marriage	Age at which ever married women aged between 15–49 years get married
Education	Educational attainment of female respondents 0 = No Education 1 = Primary 2 = Secondary 3 = Tertiary
Residence	Area of residence 0 = Urban 1 = Rural
Region	1 = Western 2 = Central 3 = Greater Accra 4 = Volta 5 = Eastern 6 = Ashanti 7 = Brong Ahafo 8 = Northern 9 = Upper East 10 = Upper West

Table 1	continuation
Variable	**Description**
Ownership and use of bank accounts	Financial Inclusion 0 = No bank account 1 = Has and uses a bank account
Wealth	The index is a proxy for income and is based on assets (e.g., television, bicycle) housing characteristics, water and sanitation characteristics 1 = Lowest 2 = Second 3 = Third 4 = Fourth 5 = Fifth
Contraceptive use	0 = Never used contraceptives 1 = Ever-used contraceptives
Marital Status	0 = Never Married 1 = Ever Married

Note: Age squared variable is used to account for the non-linearity associated with age-related variables.
Source: GMHS author's calculation

1.3 Statistical Framework

Total fertility rate (TFR) which measures the average number of births a group of women would have by the time they reach age 50 if they were to give birth at the current age-specific fertility rates was used to estimate the current fertility level of ever-married women (Croft et al., 2018).

TFR was calculated as:

$$TFR = \sum_{\alpha=15-19}^{45-49} ASFR \times 5 \,, \tag{2}$$

where, ASFR is the age-specific fertility rate for ever-married women whose age corresponds to the five-year age groups covering the reproductive years 15–49. As a convention, the following five-year age groups were used (15–19, 20–24, 25–29, 30–34, 35–39, 40–44, and 45–49). The ASFR was calculated as the number of live births per 1000 ever-married women in a specific age group (in five-year age groups) in the period 1 to 36 months preceding the 2017 GMHS, divided by the number of women of that age group in the same period. ASFR is calculated as follows:

$$ASFR = \frac{b_i}{p_i} \times 1000 \,, \tag{3}$$

where, b_i is the number of live births to ever-married women in a specified age group i and p_i is the number of women in the same age group i (15–19, 20–24, 25–29, 30–34, 35–39, 40–44, and 45–49). ASFRs were calculated for the three years preceding the 2017 GMHS survey based on interview date and detailed birth histories (i.e., birth date of each woman (whether or not she has given birth) and birth dates of children). TFRs were computed using a Stata module by Schoumaker (2013).

1.4 Generalized Poisson Regression Model

Total fertility of a woman is often modeled using children ever born (CEB) data as the dependent variable. The relationship between total fertility and other socioeconomic and demographic variables of women was modeled using the generalized Poisson regression (GPR) model given by Frome et al. (1973), and proposed by Famoye (1993). The distribution of the generalized Poisson regression model has a probability density function given by:

$$f(y_i,\alpha,\mu_i)=\left(\frac{\mu_i}{1+\alpha\mu_i}\right)^{y_i}\frac{(1+\alpha y_i)^{y_i-1}}{y_i!}\exp\left[\frac{-\mu_i(1+\alpha y_i)}{1+\alpha\mu_i}\right],\ y=0,1,2,3,\ldots n\,, \tag{4}$$

where, α is a dispersion parameter and the expected value and variance of the CEB count variable (y) conditional on a set of explanatory variables x_i (age, age at first marriage, women's educational level, women's income, women's employment status, area of residence, etc.,) is modeled as:

$$E(Y_i\,|\,x_i)=\mu_i\,, \tag{5}$$

$$V(Y\,|\,x_i)=\mu_i(1+\alpha\mu_i)^2\,. \tag{6}$$

When the dispersion parameter α = 0, the probability function in (2) reduces to the Poisson regression (PR) model. When α>0, the GPR model represents CEB count data with over-dispersion and when α<0, the GPR model represents CEB count data with under-dispersion.

The mean of the dependent variable (CEB) is denoted as $\mu_i=\mu_i(x_i)=\exp(x_i\beta)$, where x_i is a (k–1) dimensional vector of covariates and β is a k dimensional vector of regression coefficients. The estimation of the regression coefficients β is obtained by the maximum likelihood approach. The log-likelihood function of the GPR model is written as:

$$\text{Ln }L(\alpha,\beta;y_i)=\left[y_i\log\left(\frac{\mu_i}{1+\alpha\mu_i}\right)+(y_i-1)\log(1+\alpha y_i)-\frac{\mu_i(1+\alpha y_i)}{1+\alpha\mu_i}-\log(y_i!)\right]. \tag{7}$$

1.5 Goodness of Fit and Test for Dispersion

The PR and GPR models were compared using the Akaike Information Criterion (AIC; Akaike, 1974) and the Bayesian Information Criterion (BIC; Schwarz, 1978) goodness-of-fit measures defined as:

$$AIC=2k-2\ln(L), \tag{8}$$

$$BIC=k\ln(n)-2\ln(L), \tag{9}$$

where, L is the likelihood function, k is the number of estimated parameters in the model. The best model was selected based on the minimum AIC and BIC values.

The adequacy of the GPR model over the PR model was assessed by testing the following hypothesis:

$$H_0:\alpha=0,\ H_a:\alpha\neq 0. \tag{10}$$

This test of hypothesis determines whether the dispersion parameter (α) is statistically different from zero. The rejection of H_0 recommends the use of the GPR model rather than the standard Poisson regression model. The asymptotic normal Wald t-statistic was used to test for the significance of the dispersion parameter. The statistic is computed as:

$$W = \frac{\hat{\alpha}}{se(\hat{\alpha})}, \tag{11}$$

where, $\hat{\alpha}$ is the maximum likelihood estimate of α and *see* $(\hat{\alpha})$ is its corresponding standard error. The Wald t-statistic was compared with the t-distribution with $n–k–1$ degrees of freedom, where k is the total number of parameters in the GPR model.

Interpretation of the coefficients of the generalized Poisson regression model was done using incidence rate ratios (IRRs). The IRRs were obtained by exponentiating the regression coefficients of the generalized Poisson Regression model.

All analyses were conducted using Stata version 14.0 (StataCorp, College Station, Texas 77845 USA).

2 RESULTS

2.1 Current Fertility and Trends

The results from the descriptive statistics showed that the mean number of children ever born (CEB) to ever-married woman age 15–49 during the 2017 Ghana Maternal Health Survey (GMHS) was 3.2 (Table 2). The results also indicate that the mean age among women was 33.8 years and the mean age

Table 2 Description of key characteristics used in the analysis (sample size = 17 126)

Characteristics	Proportion of 1's	Characteristics	Proportion of 1's
Age		**Area of residence**	
15–19	0.0236	Urban	0.5137
20–24	0.1217	Rural	0.4863
25–29	0.1900		
30–34	0.1977	**Region**	
35–39	0.1863	Western	0.1246
40–44	0.1430	Central	0.0918
45–49	0.1349	Greater-Accra	0.1688
Mean ± σ : 33.78 ± 8.25		Volta	0.0822
		Eastern	0.1014
Age at first marriage		Ashanti	0.1878
>15 years	0.0953	Brong Ahafo	0.0961
15–19 years	0.4076	Northern	0.0822
20–24 years	0.3079	Upper-East	0.0382
<24 years	0.1893	Upper-West	0.0269
Mean ± σ : 20.26 ± 5.02			
		Contraceptive use	
Education		Never used contraceptive	0.7057
No Education	0.2546	Ever used contraception	0.2943
Primary	0.5643		
Secondary	0.1179	**Financial inclusion**	
Tertiary	0.0633	Has no account at the bank	0.3199
Children ever born (CEB)		Has and uses account at the bank	0.6801
Mean ± σ : 3.22 ± 2.18			

Table 2 continuation

Characteristics	Proportion of 1's	Characteristics	Proportion of 1's
		Contraceptive use	
Education		Never used contraceptive	0.7057
No Education	0.2546	Ever used contraception	0.2943
Primary	0.5643		
Secondary	0.1179	**Financial inclusion**	
Tertiary	0.0633	Has no account at the bank	0.3199
Children ever born (CEB)		Has and uses account at the bank	0.6801
Mean $\pm\sigma$: 3.22 $\pm$ 2.18			
Wealth Quintile			
Lowest	0.1839		
Second	0.1976		
Third	0.2003		
Fourth	0.2090		
Fifth	0.2091		

Source: GMHS author's calculation

at first marriage was 20.3 (Table 2). The low age at first marriage suggests a high level of fertility among the respondents in the survey. The results further revealed that about a quarter (26%) of the women aged between 15 and 49 years had no formal education and more than half (56%) of the sampled women had primary education (Table 2). This partly explains why the age at first marriage is quite low, since women with low levels of education are more likely to marry earlier than their more educated counterparts. Arguably, women who marry at a younger age are also likely to give birth to more children than women who marry at a late age. Table 2 also shows that, about 15% of the women interviewees within the childbearing age of 15–49 years, were living in the three Northern Regions of Ghana (Northern, Upper East and Upper West), where prevalence of poverty is the highest in the country. In addition, about 49% of the sampled women lived in rural areas, which was also observed to have a higher poverty rate than urban areas. The proportion of women in the poorest wealth quintile was about 18% (Table 2). It is worth noting that a large proportion (71%) of the women had never used any family planning method (Table 2). This may probably be due to the fact that socio-cultural, religious norms and practices impact significantly on the use of contraception in most developing countries, including Ghana.

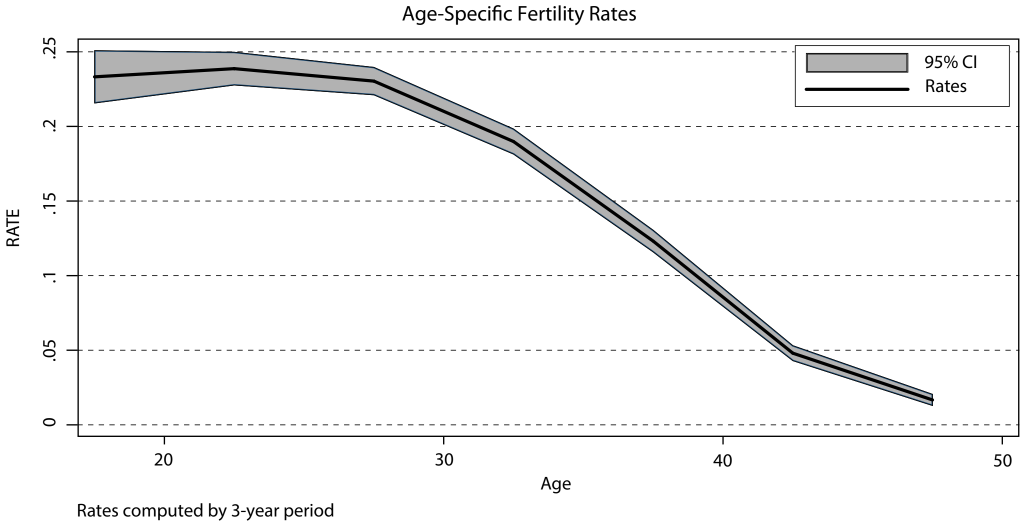
The results in this study also showed that age-specific fertility rates (ASFRs) for the 3 years preceding the 2017 survey peaked among women between 25 and 29 years and declined with age thereafter (Figure 1). This is a clear indication that, starting from age 15, a woman's fertility increases up to a point and then declines. Total fertility rates (TFRs) for the three years preceding the 2017 survey and the mean number of children born to ever married women aged between (15–49 years) for some key socio-demographic characteristics are presented in Table 3. The results indicate that the overall total fertility rate for ever-married women in Ghana is 5.4 children per woman, with rural women having 5.7 children compared to 5.1 children for urban women (Table 3). This is a slight decrease from 5.9 children per woman in 2014 (DHS 2014 – the preceding demographic health survey) which indicates that on average, a woman who has ever been married in Ghana is likely to give birth to 5.4 children by the end of her child bearing years, with higher fertility levels for women living in the rural areas. The high level of fertility rate among ever-married women has important implications for family planning. Ever married women with no formal education have a higher TFR of 6.0 compared to those with tertiary level of education, who have a TFR of 4.8 (Table 3). This indicates that the lower the level of a woman's educational attainment, the more children she is likely to bear over her lifetime and vice versa. It also means that, the TFR of women in this study is inversely related to their educational attainment. Regional differences in TFR were also observed among the women within the child bearing age range of 15–49. The results showed that the Northern Region had the highest fertility rate of 6.7 compared to 4.6 for the Greater Accra Region (Table 3). This may probably be due to prevailing factors such as the low use of and/or access to contraceptives, persistent poverty, low levels of education, early marriages and religious and cultural factors in the Northern Region. Results from this study also indicate that, in Ghana the TFR for women who have ever been married decreases with increasing wealth, from 6.5 births among women in the poorest wealth quintile to 4.4 births among women in the richest wealth quintile (Table 3). These results point to a negative relationship between household wealth and fertility of women in their child bearing years. The results further showed that, contrary to expectations, fertility trends among ever married women in Ghana has increased by about 15% from 4.6 births per woman in 2002 to 5.4 births per woman in 2017 (Figure 2). This may probably be due to the low levels of contraceptive use, cultural and religious beliefs among married women in most parts of sub-Saharan Africa, including Ghana.

Table 3 Total fertility rate and mean number of children ever born (CEB) to ever-married women age 40–49, according to background characteristics, Ghana MHS 2017

Characteristics	Total fertility rate (TFR)	Mean number of CEB to ever-married women age 40–49
Education		
No education	6.0	5.6
Primary	5.3	4.5
Secondary	4.6	3.1
Tertiary	4.8	2.7
Area of residence		
Urban	5.1	3.9
Rural	5.7	5.6
Region		
Western	5.7	4.9
Central	5.6	5.2
Greater Accra	4.6	3.4
Volta	5.4	4.7
Eastern	5.2	4.6
Ashanti	5.5	4.6
Brong-Ahafo	5.3	5.1
Northern	6.7	6.3
Upper East	5.7	5.5
Upper West	5.6	5.9
Wealth Quintile		
First	6.5	6.3
Second	5.7	5.5
Third	5.2	4.9
Fourth	4.8	4.1
Fifth	4.4	3.1
Total fertility rate (TFR)	5.4	4.7

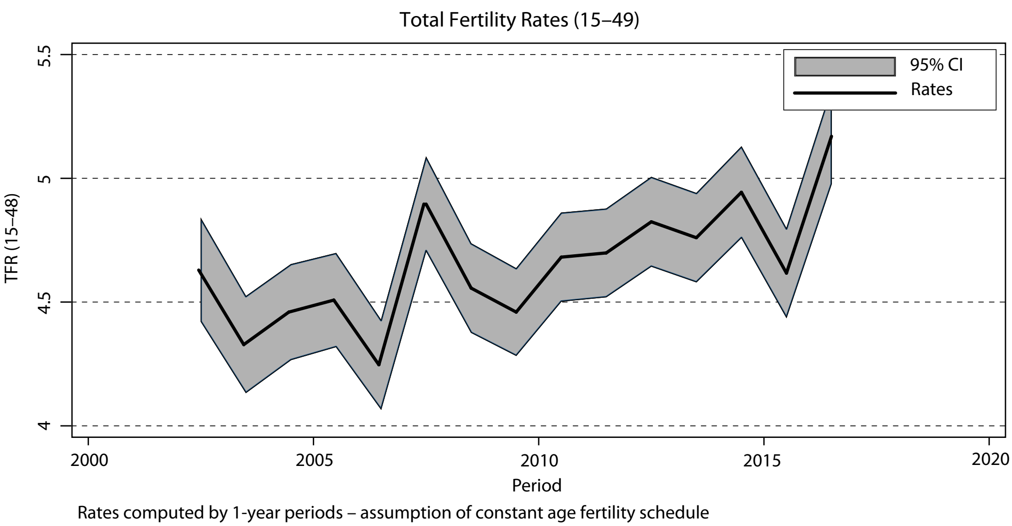
Note: Total fertility rate (TFR) of ever-married women for age 15–49 years are for the periods 1–36 months prior to interview.
Source: GMHS author's calculation

Figure 1 Age-specific fertility rate for the 3-year period preceding the survey, Ghana 2017 MHS



Source: GMHS author's calculation using the TFR STATA module by Schoumaker (2013)

Figure 2 Total marital fertility rate (15–49) for the 15 calendar years preceding the survey, Ghana 2017 MHS



Source: GMHS author's calculation using the TFR STATA module by Schoumaker (2013)

2.2 Multivariate analysis of fertility: comparison of the Poisson and Generalized Poisson Regression Models

The regression coefficients of the parameters, their standard errors and z-values of both the PR and the GPR models are presented in Table 4. Goodness-of-fit measures such as Akaike's Information Criteria (AIC) and the Schwarz's Bayesian Information Criteria (BIC) are also given in Table 4. The results showed similar parameter estimates for both models, with the GPR depicting lower standard errors compared to the PR (Table 4). This means that although estimates from both models are consistent, the GPR model obtained more precise estimates of the relationship between total household fertility and its determinants than the PR model. Estimates for the goodness-of-fit measures (AIC and BIC) also showed that the GPR model provided a better fit for the household fertility data than the PR model. For instance, the GPR model had smaller AIC (GPR = 57 072.32; PR= 58 344.53) and BIC (GPR = 57 258.28; PR = 58 522.747) values than the PR model (Table 4). The results further revealed that, in both the PR and GPR models, almost all the variables used in the study were significant at $p<0.05$ level for six (6) out of ten regions, with the exception of the Eastern, Ashanti, Brong Ahafo and Northern Regions (Table 4). The results also showed that, the variables: age; having and using a bank account; living in a rural area; and using a family planning method; have significant and positive effects on total fertility (Table 4). This suggests that, for example, the total fertility rate of women living in rural areas may be higher than that of their counterparts living in the urban areas.

The results of the test for the dispersion parameter (δ) which shows whether the mean is greater, equal to or less than the variance are presented in Table 5. The results showed that the estimated dispersion parameter from the generalized Poisson regression model was negative (–0.2360), which is an indication of under-dispersion (Table 5). This means that the variance of the Poisson distribution was smaller than its mean suggesting that there was less variation in the data than predicted. The asymptotic chi-square distribution of the likelihood ratio test statistic with 1 degree of freedom for testing the null hypothesis of (δ) = 0 was 1 274.21 and the dispersion parameter which is used to assess the adequacy of the GPR model over the PR model, was significantly different from zero ($p<0.001$, Table 5), indicating that the PR is not a suitable model for the 2017 Ghana household fertility data used.

Table 4 Determinants of fertility: estimates of Poisson and Generalized Poisson Regression Models

Characteristic	Poisson Regression (PR)			Generalized Poisson Regression (GPR)		
	Estimate	Standard error (SE)	*Wald z*-value	Estimate	Standard error (SE)	*Wald z*-value
Constant	–2.6146	0.0918	–28.47*	–2.6216	0.0734	–35.69*
Age	0.2219	0.0051	43.29*	0.2189	0.0041	53.36*
Age squared	–0.0024	0.0001	–34.09*	–0.0024	0.0001	–41.64*
Age at first marriage	–0.0323	0.0010	–33.82*	–0.0300	0.0008	–39.75*
Education						
No education (ref)						
Primary	–0.0690	0.0108	–6.36*	–0.0709	0.0089	–8.00*
Secondary	–0.2478	0.0202	–12.28*	–0.2600	0.0165	–15.80*
Tertiary	–0.2613	0.0278	-9.39*	–0.2848	0.0228	–12.51*
Area of residence						
Urban (ref)						
Rural	0.0338	0.0110	3.07*	0.0352	0.0089	3.96*
Region						
Western (ref)						
Central	0.0372	0.0184	2.02*	0.0441	0.0150	2.94*
Greater Accra	–0.0879	0.0181	–4.86*	–0.0854	0.0148	–5.79*
Volta	–0.0704	0.0190	–3.69*	–0.0677	0.0156	–4.33*
Eastern	–0.0296	0.0181	–1.63	–0.0238	0.0148	–1.60
Ashanti	0.0161	0.0159	1.01	0.0216	0.0130	1.67
Brong-Ahafo	–0.0177	0.0183	–0.97	–0.0179	0.0150	–1.19
Northern	0.0230	0.0195	1.18	0.0185	0.0161	1.15
Upper East	–0.1664	0.0258	–6.45*	–0.1360	0.0188	–7.22*
Upper West	–0.0866	0.0280	–3.09*	–0.0843	0.0231	–3.65*

Table 4						continuation
Characteristic	Poisson Regression (PR)			Generalized Poisson Regression (GPR)		
	Estimate	Standard error (SE)	*Wald* *z*-value	Estimate	Standard error (SE)	*Wald* *z*-value
Wealth Index						
Lowest (ref)						
Second	−0.1125	0.0139	−8.11*	−0.1045	0.0114	−9.17*
Third	−0.1891	0.0155	−12.22*	−0.1788	0.0125	−14.28*
Fourth	−0.2803	0.0174	−16.08*	−0.2772	0.0143	−19.41*
Fifth	−0.3772	0.0207	−18.22*	−0.3721	0.0169	−21.97*
Contraceptive use						
Never used contraceptive (ref)						
Ever used contraceptive	0.1421	0.0095	14.89*	0.1255	0.0079	15.95*
Financial inclusion						
Has no account at bank (ref)						
Has and uses account at the bank	−0.0783	0.0115	−6.81*	−0.0717	0.0092	−7.82*
Goodness-of-fit						
Log-likelihood		−29 149.2640			−28 512.1610	
AIC		58 344.5300			57 072.3200	
BIC		58 522.7400			57 258.2800	

Note: * significant at $p<0.05$ level
Source: GMHS author's calculation

Table 5 Test for dispersion for a Generalized Poisson Regression Model

Statistic	Estimate
Dispersion parameter (δ)	−0.2099±0.0048
Likelihood-ratio test of (δ) = : chi2(1)	1 274.2100
Prob> = chi2	0.0000

Source: GMHS author's calculation

2.3 Demographic and socio-economic determinants of fertility

For an easy interpretation of the regression coefficients of the explanatory variables used, incidence rate ratios (IRR) of the generalized Poisson regression model are presented in Table 6. The results showed that age was significant ($p<0.05$) and positively related to the number of children ever born to ever married women in this study (Table 4). This indicates that number of children ever born to women increases with age. The coefficient of age squared was also significant at $p<0.05$ and indicates that the relationship between age and number of children ever born to women is not linear. The positive coefficient for age and the negative coefficient for age squared suggest that number of children ever born increases with age until it reaches a point (peak) and then declines thereafter. Based on the IRR results in Table 6, on average, a one year increase in age increased the number of children ever born to a woman by a factor of 1.2447 or 25%, holding all other variables constant and the effect was statistically significant at ($p<0.05$).

A woman's age at first marriage was inversely related to the number of children ever born and significant at $p<0.05$ (Table 4). The results further showed that a one year increase in age at first marriage reduced the number of children ever born by a factor of 0.9705 or 3%, while holding all other variables constant

(Table 6). This implies that as age at first marriage increases, the number of children ever born to a woman decreases. The results further revealed that, a woman's highest educational level was statistically significant and negatively related to the number of children ever born (Table 4), indicating that more educated women have less children. Based on the results in Table 6, women with tertiary education had about 25% less children than women with no education. This suggests that women with no formal education or low levels of education are likely to have more children than their highly educated counterparts.

The results also showed that the effect of women who reside in rural areas on the number of children ever born was significant ($p<0.05$) and positive. This indicates that women in rural areas give birth to more children on average than women who reside in urban areas. A finding that may be attributable to factors such as: low levels of education; early ages at first marriage; no or low use of contraceptives; and low standards of living. Regional differences were also observed for number of children ever born to ever married women in this study. For instance, the results in Table 6 indicate that ever married women who live in the Northern region of Ghana had about 2% more children than those living in the Western region.

The generalized Poisson regression analysis also showed that wealth index (type of consumer goods owned) was significantly ($p>0.05$) and inversely related to the number of children ever born (Table 4). Rich women had 31% less children than poor women (Table 6). This implies that, as the wealth index increases, women who are in the richest wealth quintile are more likely to have less children than those in the poorest wealth quintile.

The analysis further showed that the effect of having and using a bank account on the number of children ever born to ever married women was negative and statistically significant (Table 4). Women who had accounts at banks or financial institutions had about 7% less children than those who did not have and use a bank account (Table 6). This shows that women who are economically empowered have less children than those who are not. This is because economically empowered women tend to have greater access to income and equal opportunities in decision making, especially relating to the number of children they want to have.

The results also showed that the effect of contraceptive use on the number of children ever born was positive and significant ($p<0.05$, Table 4). Women who had ever used contraceptives had 13% more children than those who had never used contraceptives. One good reason for this paradox could be that ever-married women in Ghana only use contraceptives when they have had their desired number of children, indicating low contraceptive prevalence in this study.

Table 6 Incidence Rate Ratios: Generalized Poisson Regression Model

Characteristic	Incidence Rate Ratios (IRR)		
	Estimate	**Standard error (SE)**	***Wald z*-value**
Constant	0.0727	0.0053	–35.69*
Age	1.2447	0.0051	53.36*
Age squared	0.9976	0.0001	–41.64*
Age at first marriage	0.9705	0.0007	–39.75*
Education			
No education (ref)			
Primary	0.9316	0.0083	–8.00*
Secondary	0.7710	0.0127	–15.80*
Tertiary	0.7521	0.0171	–12.51*
Area of residence			
Urban (ref)			
Rural	1.0359	0.0092	3.96*

Table 6 continuation

Characteristic	Incidence Rate Ratios (IRR)		
	Estimate	Standard error (SE)	*Wald z*-value
Region			
Western (ref)			
Central	1.0450	0.0157	2.94*
Greater Accra	0.9181	0.0135	–5.79*
Volta	0.9345	0.0146	–4.33*
Eastern	0.9765	0.0145	–1.60
Ashanti	1.0219	0.0133	1.67
Brong-Ahafo	0.9823	0.0148	–1.19
Northern	1.0187	0.0164	1.15
Upper East	0.8728	0.0164	–7.22*
Upper West	0.9192	0.0212	–3.65*
Wealth Quintile			
Lowest (ref)			
Second	0.9007	0.0103	–9.17*
Third	0.8363	0.0105	–14.28*
Fourth	0.7579	0.0108	–19.41*
Fifth	0.6893	0.0117	–21.97*
Contraceptive use			
Never used contraceptive (ref)			
Ever used contraceptive	1.1338	0.0089	15.95*
Financial inclusion			
Has no account at bank (ref)			
Has and uses account at the bank/financial institution	0.9308	0.0085	–7.82*
Goodness of fit tests			
Log-likelihood		–28 512.1610	
AIC		57 072.3200	
BIC		57 258.2800	

Note: * significant at $p<0.05$ level
Source: GMHS author's calculation

3 DISCUSSION

The study estimated current fertility levels and trends of ever married women in Ghana and assessed the influence of socio-economic and demographic characteristics on household fertility using the generalized Poisson regression model.

3.1 Current fertility and trends

Total fertility rate (TFR) is a standard measure of population growth that has been widely used to measure the average number of children per woman during her reproductive years. Currently, fertility rates are declining globally, however, marked differences between fertility levels in developed and developing countries have been observed, with an estimated high total fertility rate of 4.6 births per woman in sub-Saharan African compared to about 1.6 births per woman in developed countries (UN DESA, 2020). Possible reasons given for the high fertility rates in sub-Saharan countries include low use of contraceptives, early marriages and generally lower levels of female education (Nargund, 2009). The high fertility rates observed in sub-Saharan countries is purported to give rise to continued rapid population growth, poverty, low educational attainment, low family incomes, poor health, and lack of access to education (Birdsall and Griffin, 1988; Trends, 2017). The results in this study indicate that the TFR of 5.4 children per woman among ever married women in Ghana is high. The results also showed substantial socioeconomic and geographical variations in fertility rates. For instance, the fertility rate among women who resided in rural areas (5.7) was relatively higher than those who dwelt in urban areas (5.1). Similar results have been reported by Shapiro and Tambashe (2002) for sub-Saharan Africa.

Contrary to numerous reports on declining global fertility trends (UN DESA, 2017), stalling fertility trends – "a change from downward fertility trends to flat or even slightly rising trends for usually a few years" (Garenne, 2008) have been observed in sub-Saharan Africa (Schoumaker, 2019; Sayi, 2015; Agyei-Mensah, 2007). The fertility trend in this study depicts a slightly rising trend, with an increase of about 15% from year 2002 to year 2016. The results are consistent with findings by Shapiro and Gebreselassie (2007), Garenne (2008), and Bongaarts (2006) which show stalling of fertility decline based on fertility data from some countries in sub-Saharan Africa. Likely causes of stalled fertility declines observed in sub-Saharan Africa have been associated with demographic, socio-economic and proximate determinants of fertility such as decline in income per capita, less contraceptive use, low child mortality and stall in trends of education (Bongaarts, 2006; Kebede et al., 2019).

3.2 Multivariate analysis of fertility: comparison of the Poisson and Generalized Poisson Regression Models

In situations where under-dispersion or over-dispersion occur in the analysis of count data, Wang and Famoye (1997), Famoye (2015), Singh (2000), and Harris and Yang (2012) suggest that the use of the generalized Poisson regression model provides a better alternative to the standard Poisson regression model. The reasons being that GPR is able to adequately accommodate for under-dispersion or over-dispersion in the analyses of count data and that GPR has statistical advantages over the standard Poisson regression model. Multivariate analysis of this study revealed that the estimated dispersion parameter in the GPR model was negative and significant at $p<0.05$. This means that the conditional variance of the dependent variable (number of children ever born) given selected explanatory variables was significantly smaller than the associated conditional mean (an indication of under-dispersion) and implies that the generalized Poisson regression model is an appropriate model for the fertility data used in the study. The results further revealed that although both models provided similar parameter estimates, the standard errors of the PR model were over-estimated due to the presence of under-dispersion. Furthermore, the smaller values of the goodness-of-fit measures (AIC and BIC) for the GPR model showed that it offered a better fit to the data compared to the standard Poisson regression model. These results are consistent with findings by Wang and Famoye (1997), and Harris and Yang (2012) who modeled under-dispersed count data using the generalized Poisson model.

3.3 Demographic and socio-economic determinants of fertility

Typically, the educational attainment of a woman is expected to be directly related to her opportunity cost of time and inversely related to her fertility decision (Becker, 1981; Wang and Famoye, 1997). The results of this study indicate that the educational level of ever married women was statistically significant and negatively related to fertility. This suggests that the higher the educational level of a woman the less children she is likely to bear during her lifetime. These results are consistent with empirical evidence reported by Ali and Gurma (2018), and Monstad et al. (2008). Contrary to expectations, a number of studies have revealed that education does not have a uniform inverse relationship with fertility. Empirical findings indicate that conditioned on "society's socio-economic development, social structure, cultural context and stage in the fertility transition", education is positively related with fertility at lower levels of education in sub-Saharan Africa (Martin, 1995). Others have also found that education's relationship with fertility is generally weak in poor, illiterate and rural societies and grows stronger in more prosperous societies (Diamond et al., 1999; United Nations, 1995).

The average woman's best reproductive years are in her 20s and gradually decline in the 30s, particularly after age 35 (Dunson et al., 2002). Age at first marriage is therefore an important determinant of fertility for ever-married women and has important implications for population growth (Bongaarts et al., 1984). According to results from a United Nations report, a younger age at marriage is associated with high fertility rates because women who marry at younger ages are exposed to a longer childbearing period and are likely to bear more children than their older counterparts (UN DESA, 2014). The results in this study showed that a woman's age at first marriage was significantly and inversely related to her fertility. This suggests that women who marry at a younger age are likely to give birth to more children than women who marry late. Similar results have been reported by Nag and Singhal (2013), Palamuleni (2011), Solanke (2015), Kabir et al. (2001), Bongaarts (1982).

Rural–Urban fertility differences have been found in a number of studies, making area of residence a major determinant of fertility (Shapiro and Tenikue, 2017; Eloundou-Enyegue and Giroux, 2012; Casterline, 2015; Yousif, 2001). Women who live in rural areas are expected to have more children than those who live in urban areas because of the *high* direct financial cost of raising children in urban areas and the opportunity costs involved in moving the children from farm to urban areas (Learch, 2019). According to Becker (1976, p. 190), it is cheaper to raise children on a farm than in an urban community. The results of this study showed that the relationship between women who resided in rural areas and fertility was significant and positive, indicating that women who live in rural areas have higher fertility than urban women. This is in agreement with studies by Casterline (2015), and Yousif (2001; 1996) who suggest that low levels of education, low use of contraceptives and early marriages by rural women could be possible reasons for the rural-urban differences in fertility.

The relationship between wealth and fertility vary substantially across societies, with a more positive effect in high fertility areas (Colleran and Snopkowski, 2018). A significant and inverse relationship between household wealth and fertility was observed in this study. This finding indicates that women in the poorer quintiles are likely to give birth to more children thereby having higher fertility than women in the richer quintiles. Similar results have been reported (Mansanja et al., 2016; Colleran and Snopkowski, 2018) and are also in line with Becker and Lewis's economic fertility model that predicts a likely substitution effect from quantity to quality of children with rising family wealth. A possible reason could be that poor women consider children as household assets and forms of investment, thus egging them on to have more children. Conversely, other studies have found that the relationship between wealth and fertility is much more likely to be positive than negative (Stulp and Barret, 2016). This variation may generally be associated with cultural, religious, demographic and socio-economic backgrounds that pertain in different societies (Higgins, 2015; Ezeh et al., 2009; Stulp and Barret, 2016).

Empirical analyses have also shown that at higher levels of financial development, women prefer to trade quantity of children for quality of children (Idris et al., 2018). Studies by Becker and Lewis (1973), and Wang and Famoye (1997), have emphasized that an increase in quality per child implies an increase in costs of raising a child which decreases fertility. The results of this study revealed that ownership and use of bank accounts by an ever-married woman was significantly and negatively related to fertility. The results suggest that a woman's ownership and use of a bank account is associated with lower fertility. Studies by Filoso and Papagni (2011), Lehr (1999), Cigno and Rosati (1992) have confirmed that having access to the financial market is inversely related to the fertility decisions of women. One explanation for the inverse relationship between a woman's ownership and use of a bank account and fertility is that, as her financial situation improves, a woman prefers to have less but higher quality children.

Several studies have established that an inverse relationship exists between contraceptive use and fertility rates with women who ever used contraceptives having less children than those who never used contraceptives (Becker and Costenbader, 2001; Ross and Winfrey, 2002). Contraceptive use has therefore, become a major determinant of fertility due to its ability to reduce the world's total fertility rate (Creanga et al., 2011). Contrary to these findings, results in this study showed that women who had ever used contraceptives had more children ever born than those who did not use contraceptives, suggesting that they probably used contraceptives after they had their desired number of children. Similar patterns have been observed in studies by Gyimah et al. (2012), UN DESA (2015), Howse and Nanitashvili (2014), and Wang et al. (2017). The positive relationship between contraceptive use and fertility among ever-married women in sub-Saharan Africa, primarily results from sociocultural factors that undermine the relevance of family planning services and encourage high levels of fertility (Gyimah et al., 2012; Ekane, 2013).

CONCLUSION

Undertaking research to acquire information on the key socio-economic and demographic factors that influence fertility trends and dynamics is essential in monitoring population growth and developing policies and programs that aim at managing a nation's population. This study estimated the current fertility level and trend of ever-married women between the ages of 15 and 49 years and modeled the socio-economic and demographic determinants of household fertility using the generalized Poisson regression model. The results presented showed that the current fertility level for ever-married women in Ghana is 5.4, which is quite high according to United Nations (UN) underlying definition which states that, "high fertility is total fertility levels above 5 children per woman". In addition, a stall in fertility trend was observed which is consistent with previous results in sub-Saharan African countries. The generalized Poisson regression model was used to identify some of the key socio-economic and demographic factors influencing the high fertility level and stall in fertility trend. The results revealed that, lack or low levels of education, early ages at first marriage, belonging to the poorer household wealth quintiles, dwelling in a rural area, not using contraceptives, not owning and using a bank account contributed to the high fertility level observed in this study. The multivariate analysis has thus provided a clearer picture of the key socio-economic and demographic factors influencing the high fertility level than can be obtained from analysis of total fertility rates.

It is recommended that, cross-sectoral engagement between the National Population Council and the ministries responsible for health, education, gender and employment can help decision-makers to design efficient and effective coherent policies aimed at reducing the prevailing high fertility levels and hence the population growth. For instance, policies that promote longer periods spent schooling might prevent women from engaging in early marriages. Early marriages, generally expose women to a longer childbearing period which can result in high fertility rates. Promotion of higher educational attainment levels may also offer better access to economic and social opportunities. At medium or high levels of economic and social development, children will no longer be considered as economic assets and forms of investment as economically advantaged women will substitute quantity of children with quality. Perhaps, more educated women who have better access to economic and social opportunities may take control of their fertility decisions by using contraceptives to reduce high fertility levels and hence population growth. Lastly, empowering women through financial inclusion (e.g., owning and using a bank account) could help women to make their own fertility decisions and have less children.

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The Czech *2021 Population and Housing Census*

On Tuesday 11 May, the 2021 Census, the largest statistical project of the decade, finished in the Czech Republic. It was organised by the Czech Statistical Office (CZSO). Extraordinary effort of people and use of technologies, especially in the real operation phase that lasted for 46 days, from 27 March to 11 May, were devoted to it. Throughout the whole period of the Census, it was possible to fill in the census form (questionnaire) online; from 17 April, paper census forms (questionnaires) were also available.

What was highlighted this year most of all was an opportunity to get counted (enumerated) online, which turned out to be a significant advantage during the coronavirus pandemic, which was not taken into account at all, naturally, during most of the time of the project preparation. According to the opinion poll of the Kantar agency carried out this January, 71% of people were considering the online form to get counted; however, it is estimated that in the end 87% of the population filled in electronic census forms (questionnaires) and sent them. The Population Census is thus the largest IT project, in which the biggest number of inhabitants of the Czech Republic participated so far. Not only the epidemic situation but also the easy and fast way to complete the electronic census form (questionnaire) contributed to that.

In average, people spent 20 minutes and 34 seconds by filling in (completing) the electronic census form (questionnaire) for a household and thus they saved 9 minutes compared to the paper census form (questionnaire). They saved some more time because they did not have to wait for the census officer (census enumerator) or bring the paper census form (questionnaire) to the post box or to a Census contact point.

In total, 4 217 261 electronic census forms (questionnaires) and over 683 000 paper census forms (questionnaires) were submitted as at 11 May. However, only during their processing it will be made clear how many dwellings (flats), households, and persons got counted (enumerated) by them. It is because the paper census forms (questionnaires) have to be scanned, digitalised, first of all, quality of filled in data must be checked, and further data from administrative data sources must be matched with all of them, i.e. also with the electronic ones. Only then will personal data be erased from all the forms, i.e. birth certificate numbers (“*rodné číslo*” in Czech), names, surnames, and document numbers (ID card numbers). All these actions require time, i.e. weeks up to months. Only after that starts processing of statistics. Therefore results cannot be published before the turn of the year.

To log in into the electronic census form (questionnaire), 64% of users used a computer and 36% a mobile phone or a tablet. Electronic census forms (questionnaires) had been prepared in 7 language versions so that also foreigners and members of national minorities could get counted (enumerated) without problems.

Intensive preparations for this year’s Census project started already in 2014 with the aim to facilitate the situation to all who are getting counted (enumerated) as much as possible. Therefore, since the very beginning, there was an effort to maximally use data stored in various registers and databases and to ask people only for those pieces of information that cannot be obtained in another way in the necessary quality.

For this year’s Census, data from nine public registers were successfully obtained and the number of questions was thus reduced approximately by half compared to 2011. A form (questionnaire) to find out information about buildings (houses) was entirely eliminated.

Contrary to the original plan, when the Online Census was to be only made available for the first 14 days, however, the opportunity to get counted (enumerated) online remained open throughout the entire period of the field phase of the Census due to the pandemic situation that was unfavourable. The system was thus continually working for 46 days and except for an outage soon after the start of real operation it reliably worked up until the end of the Census. The total score thus stands at 1096 hours without a failure to the 8-hour outage.

Paper census forms (questionnaires) were distributed to households by 10 000 census officers (census enumerators) of the Czech Post and it was also possible to pick them up and submit them at some of the 800 contact points established at branches of the Czech Post all over the Czech Republic or at 13 contact points of the Czech Statistical Office.

The Czech Statistical Office also organised 5 webinars for persons with hearing impairment in order to provide sufficient assistance to those who, for example, could not call the information line; the CZSO also ensured services of an interpreter on determined days. The census form on the website was naturally tailored for persons with visual impairment, the purblind and the blind.

Web pages *scitani.cz* were displayed over 33.5 million times and they were visited by over 5 million users. Besides the direct entry to the electronic census form (questionnaire), “Help” was the most visited page.

THE CENSUS CONTACT CENTRE

The Census Contact Centre as well as information services of the Czech Statistical Office played an important role in the Census as people were addressing their questions there. The Census Contact Centre opened on 12 March and people could call or send their questions regarding the Census by e-mail.

The Census Contact Centre, operated by the Conectart company, was in operation for almost ten weeks, daily until late evening hours, including Saturdays, Sundays, and holidays. Over 180 operators were answering the phone calls.

The Census Contact Centre, which provided information support and help with filling in the census forms (questionnaires) to the public during the whole 2021 Census received almost 270 thousand phone calls, of which 53% were processed by an automatic machine without the necessity to be assisted by a human operator. Preparatory works on an intelligent/smart and dynamic reply system for the Census were highly intensive and lasted for over two months. For the voice automatic machine, a combination of texts read by a professional speaker and a voice synthesis were used so that it was impossible to recognise that it is not a human answering the phone. Staff of the Contact Centre also answered 22 686 questions sent by e-mail.

The staff of the Contact Centre comprised 182 operators, 4 heads of project, 8 heads of teams, 10 instructors, and 5 internal auditors of quality – and satisfaction with that staff reached 92%. It thus highly surpassed the expectations as the original threshold was set at 80%. Operators were answering various questions – e.g. regarding the obligation to get counted (enumerated), specific queries about individual questions in the census form (questionnaire) up to phone calls with lonely people or people who are not satisfied with their life that lasted for many minutes.

Further 264 845 questions were answered by a chatbot – it is a unique solution and the Czech Statistical Office was among the first ones globally to use it for the needs of the Census. People could communicate with the chatbot (in Czech only) on the website *scitani.cz* and also directly in the electronic census form (questionnaire) or in the mobile application.

Operators of the Census Contact Centre and staff of the CZSO information services were successfully solving even more complicated cases when, for example, a respondent could not tell whether he/she is also obliged to get counted (enumerated) or when he/she tried to use a type of papers (ID) not suitable for logging in. Such cases were solved case by case. It also applied to cases of expired IDs without machine readable data, which were added to the system after it had been consulted with the Ministry of the Interior. Operators also helped fill in the forms over the phone while they went through the form with the caller step by step and advised to him/her what shall be entered into which place.

People were most frequently asking the centre about how to enumerate several private households that do not have common budget but live together. Frequent were also questions about how to enumerate household members working abroad, questions about confirmation that the census form (questionnaire) has been sent or whether it is possible to correct wrong data in an already sent form (questionnaire). Many people also needed help with filling in information about commuting to work and to school during the pandemic.

Besides usual questions about how to fill in the census forms (questionnaires) properly, inquirers also asked, for example, how to enumerate prisoners abroad or inhabitants of a convent. Operators of the centre often learned a lot about lives of the callers while handling the phone calls.

It was important for many respondents to know what purpose data from the Census will serve to. Some needed to receive information as to where the nearest contact point of the Census is, i.e. where it was possible to pick up census forms (questionnaires) or to submit the completed ones.

DATA FROM THE CENSUS

The 2021 Census is organised by the CZSO and its results will influence life in the Czech Republic during the next decade. The Census not only measures the population size; it is mainly indispensable for the CZSO – for it to be able to release information every year about the population change (an increase or a decrease) and about distribution of the population. On that, for example, allocation of taxes from the budget is based every year.

Mainly municipalities are interested in that because data from the Census can significantly influence life of their population. It is because the Ministry of Finance distributes tax revenues namely according to the data from the CZSO. When inhabitants do not participate in the Census, municipalities (and therefore also their citizens) can lose a big amount of money designated for their development every year.

The CZSO is also obliged to make population forecasts every five years – in order to set the pension system or due to a pension reform, in order to plan services such as construction of kindergartens or community care homes (retirement homes). That would also be impossible without data from the Census. Moreover, it is necessary to know, for example, what type of people live in a given locality – what their education is, their profession, and how far they commute to work. From that, one can tell whether there is potential labour force in some region for a certain type of enterprises, to which people would not have to commute two hours, and therefore direct investments towards there. Besides that, commutation also shows spatial territorial relationships – it means that people may belong to some Region in terms of administration, however, in reality it is obvious that they commute to work somewhere else. Therefore, the benefit of the Census for the next decade is enormous and without it we would not have essential information about ourselves. The first results will be available at the turn of this year and the next one.

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We publish articles focused at theoretical and applied statistics, mathematical and statistical methods, conception of official (state) statistics, statistical education, applied economics and econometrics, economic, social and environmental analyses, economic indicators, social and environmental issues in terms of statistics or economics, and regional development issues.

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Authors and Contacts
Rudolf Novak*, Institution Name, Street, City, Country
Jonathan Davis, Institution Name, Street, City, Country
* Corresponding author: e-mail: rudolf.novak@domainname.cz, phone: (+420) 111 222 333

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Phone: (+420) 274 052 733, (+420) 274 052 783
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