

## Hierarchical forecasts of Diabetes mortality in Mexico by marginalization and sex to establish resource allocation

Pronósticos jerárquicos de mortalidad por diabetes en México por marginación y sexo para establecer asignación de recursos

Eliud Silva  
Corey Sparks

### Abstract

*Objective:* The Mexican population has experienced an astounding rise in type II Diabetes mortality as well as a growing trend for the economic burden in the recent years. The paper's purpose is to propose an approach to establish a distribution of resource allocation objectively to face the future economic burden.

*Methodology:* Hierarchical forecasts of Diabetes mortality to 2030 by sub-domains of the population are estimated based on marginalization and sex.

*Results:* The forecasts confirm that differences related to sub-domains will be significant. In fact, the rates will increase most notably both in low and high marginalized.

*Limitations:* The hierarchical method just provide point forecast without prediction intervals.

*Originality:* There is not a similar application for Mexican data to do that objectively.

*Conclusions:* The most recommendable budget distribution should be mainly addressed among the low and high levels. Implications of these estimates should support unpostponable health policy in general and for the mentioned sub-domains in particular.

**Keywords:** Diabetes, mortality, hierarchical forecasts, marginalization, resource allocation.

**JEL Classification:** C32, C53, C46.

### Resumen

*Objetivo:* La población mexicana ha experimentado un aumento asombroso en la mortalidad por Diabetes tipo II, así como una tendencia creciente de su carga económica recientemente. El propósito del trabajo es proponer un enfoque para establecer una distribución de la asignación objetiva de recursos para enfrentar su carga futura.

*Metodología:* Se estiman pronósticos jerárquicos de mortalidad por Diabetes tipo II al 2030 por subdominios de la población por marginación y sexo.

*Resultados:* Se confirma que las diferencias de los subdominios serán significativas. De hecho, las tasas aumentarán de manera más notable en los niveles bajo y alto.

*Limitaciones:* El método solo proporciona pronósticos puntuales sin intervalos de predicción.

*Originalidad:* No existe una aplicación similar para datos mexicanos que permita hacer objetivamente tales estimaciones.

*Conclusiones:* La distribución presupuestaria más recomendable debe abordarse principalmente entre los niveles bajo y alto. Sus implicaciones deberían respaldar la política de salud impostergable en general y para los subdominios mencionados en particular.

**Palabras clave:** Diabetes, mortalidad, pronósticos jerárquicos, marginación, asignación de recursos.

**Clasificación JEL:** C32, C53, C46.

**Eliud Silva.** Universidad Anáhuac México. México. Correo electrónico: [jose.silva@anahuac.mx](mailto:jose.silva@anahuac.mx). <https://orcid.org/0000-0003-0499-0446>

**Corey Sparks.** The University of Texas at San Antonio. USA. Correo electrónico: [corey.sparks@utsa.edu](mailto:corey.sparks@utsa.edu). <https://orcid.org/0000-0003-4289-0075>

## Introduction

Over the past decades, the Mexican population has undergone the epidemiological transition, from a primarily preventable causes of death due to infection and other preventable diseases, to the emergence of an increasing degenerative causes of death. Along these lines, one primary concern is the rise in obesity and type II Diabetes (Diabetes from now on). Associated with these increasing morbidity rates, Mexico has experienced a significant expansion of the Diabetes mortality rates (Barquera, Campos-Nonato, & Hernández-Barre-ra, 2013).

Diabetes prevalence has increased among adults of every age group and it has been one of the most important causes of death in Mexico since 2000, being at least 1.6 times as often the underlying cause of death (Bustamante-Montes, Lezama-Fernández, Fernández-De Hoyos, Villa-Romero, & Borja-Aburto, 1990). These changes have had significant negative effects on life expectancy in Mexico (Agudelo-Botero & Dávila-Cervantes, 2015; Dávila-Cervantes & Pardo, 2014; Palloni, Beltrán-Sánchez, Novak, Pinto, & Wong, 2015).

The Diabetes prevalence pattern in Mexico has been extremely heterogeneous; unlike the United States, it has shown that the epidemiological transition across states has not occurred simultaneously. A group of Mexican researchers called this phenomenon the “polarization of the transition” (Frenk, Bobadilla, Sepúlveda, & López, 1989) where different regions of the country are experiencing the epidemiological transition in different ways (Frenk & Chacón, 1991a, 1991b).

There is evidence of the recent trends in the prevalence of Diabetes and its risk factors in national health surveys (Villalpando, Shamah-Levy, Rojas, & Aguilar-Salinas, 2010). From 1993 to 2006, the prevalence of Diabetes increased from 6.7% to 14.4%; to note, the relative change in mortality for the period 1980-2000 shows that the most significant increase has been main-

ly in the southern central and Mexico City regions (Barquera, Tovar-Guzmán, Campos-Nonato, González-Villalpando, & Rivera-Dommarco, 2003). This dynamic predicts larger increments in the near future for Diabetes morbidity and mortality.

At national level, the adults aged 20 years and above, with overweight and obesity was 75.2% (39.1% overweight and 36.1% obesity) in 2018, compared to 71.3% in 2012. Likewise, the states that presented the higher percentages were Campeche, Tamaulipas, Hidalgo, Mexico City and Nuevo Leon. The percentage of the population aged 20 years and above with a diagnosis of Diabetes in 2012 was 9.2% (6.4 million); by sex, 9.7% were women and 8.6% men; in 2018, it was 10.3% (8.6 million), 11.4% females and 9.1% males (Instituto Nacional de Estadística y Geografía [INEGI], Instituto Nacional de Salud Pública [INSP], & Secretaría de Salud [SS], 2019).

The purpose of the current study is to propose an objective approach to allocate resources, based on hierarchical forecasts of Diabetes mortality to 2030, using the Hyndman and Athanasopoulos (2018) method. The hierarchical time series model allows to forecast the number of deaths by Diabetes based on sub-domains of the population. It is important to recognize that the hierarchical structure is absolutely flexible and it depends on the analyst's criteria and the goal pursued.

This paper is organized as follows. The next section is devoted to the economic burden of Diabetes and different estimates made for the Mexican case. In the next section, the methodology is presented, describing how data is handled and how the model is established, in accordance with the proposed hierarchical structure. Then, the results of the forecasts are exposed from the first to the last level of the mentioned structure. Here, it is evident the coherence among the forecasts. Afterwards, the main conclusions are described and justified to highlight a new public health policy.

## Estimates economic burden of Diabetes

Diabetes has become one of the leading public health challenges of the twenty-first century due to the large economic burden and its adverse impact on the overall health of the population. This emerging morbid condition has placed increasing costs on the Mexican healthcare system. Its economic burden affects a wide range of variables, including economic and human development, as well as the conditions of equity and poverty (Barquera et al., 2013). In other words, its economic impact encompasses the direct costs associated with spending on health care, that is medical services and drugs, and indirect costs of the disease that relate to the effect of premature mortality and disability of a person to participate effectively in the labor market.

The 2013 estimates suggest that the economic burden of Diabetes was about 2.25% of the Mexican GDP. This amount is greater than the actual annual growth of the Mexican economy of 2.1%, registered by INEGI at the end of 2014, and the one projected for 2021. The direct costs of Diabetes were estimated at \$179,495.3 million pesos in 2013 (Barraza-Lloréns et al., 2015). Likewise, financially speaking, comparing the economic impact in 2012 versus 2010 Arredondo and Reyes (2013) estimated a 33% increase in costs associated to this public affection. Thus, they posited the need to review the current organization of the Mexican health system, to move from a curative health care mode to preventive models that enable a better way to deal with the expected challenges.

Most recently, Arredondo, Orozco, Alcalde-Rabanal, Navarro, and Azar (2018) estimate the economic burden of the health services demand due to Diabetes and hypertension for the Mexican insured and uninsured population in five regions. According to their results, between 2013 and 2018, the economic burden of both diseases increased between 58%-66%. They also argue that, based on their forecasts, on each of the analyzed

regions, to address these diseases, the authorities will require between 13% and 15% of the public health budget for the uninsured population and between 15% and 17% for the insured population.

To determine trends related to the economic burden from Diabetes, Arredondo et al. (2019) developed a longitudinal analysis. This analysis generated two key findings: there was a 26% increase in the economic burden from incidence from 2016 to 2018, and the total amount allocated to treat Diabetes in 2017 was \$9 684 780 574 (us dollars). Thus, they suggest reviewing and rethinking strategies of prevention, planning, organization and resource allocation.

The same analysis of economic burden of Diabetes in the elderly was made by Arredondo (2020). He compared the economic burden for 2020 versus 2022 and concluded that the increase was estimated at 29%. He also pointed that amid the coronavirus 2019 pandemic, there is a serious complication to achieve the scope of universal coverage for diabetics in Mexico. It is worth mentioning that based on the aforementioned literature, there is no proposal for the objective allocation of resources to face the economic burden, based on the deaths that occur by sub-domains of the population, and which is considered a relevant contribution of this paper.

## Methodology

### Data

Data was extracted from two sources. First, the mortality data are taken from the INEGI and the ss (1985-2017); individual level micro-data available at <https://cutt.ly/8wMbkfu>. Second, official population estimates are obtained from the Mexican population council (Consejo Nacional de Población [Conapo], 2019) available at <https://cutt.ly/jwMn6p0>. From the INEGI data, data counts of deaths by Diabetes-related causes (ICD-10 codes) were obtained for years 1985 to 2017 (the most recent data available). The (mid-year) annual

population estimates data from Conapo for the 1985 to 2030 period were considered. All these data were classified by marginalization and sex. The datasets analyzed and generated during the current study are available in **Table 1**.

The state level information was aggregated, based on the marginalization index (shown in **Figure 1**) created by Conapo in 2015 (Conapo, 2016). The index was constructed by means of Principal Components Analysis using the following variables from the Intercensal Survey (EIC) 2015 (INEGI, 2015): Illiteracy rate, % of the population without primary school completed, % of household without adequate toilet facilities, % of households without electricity, % of households without an external water source (municipal water), % of overcrowded households, % of households with dirt floor, % of the population living in rural areas, % of the population with low wages (measured as twice the minimum wage).

In short, we divide the Mexican population into two sub-domains: marginalization level and sex. Since previous work has documented the differences in Diabetes mortality by gender, forecasts must not assume a common rate for men and women. Likewise, variation by socioeconomic status of residence has also been linked to variation in Diabetes mortality within Mexico (Flores, Sparks, & Silva, 2016), so the forecast methodology will separately forecast the Diabetes deaths by level of marginalization. **Figure 1** shows the five levels subdivision of Mexican states based on the marginalization index. Very High and High levels of marginalization is typically linked to high poverty, poor housing conditions, small communities, and low socioeconomic status.

The importance of looking at regional differences on Diabetes patterns consist of the relationship with local socioeconomic status conditions. Research on the topic suggests that Diabetes is not only associated with socioeconomic characteristics at the individual level, but also at the regional level. Socioeconomic determinants such

as income, education, housing, and access to nutritious food are central to the development and progression of Diabetes. Moreover, the incidence and prevalence of Diabetes appear to be socially graded, as individuals with lower income and less education are 2 to 4 times more likely to develop Diabetes than more advantaged individuals (Hill et al., 2013). In this sense, poverty and material deprivation, defined as a lack of resources to meet the prerequisites for health, play a key role.

### Hierarchical time series model

A hierarchical time series is a collection of several time series that are linked together in a hierarchical structure (Hyndman & Athanasopoulos, 2018). In our case, the hierarchical structure to forecast is identified through **Figure 2**. The same structure, both for total deaths and for total population is used. Then, the mortality rate by Diabetes per 100 000 with these forecasts is calculated considering the denominators from Conapo's projections. According to **Figure 2**, it is necessary to construct the time series at the bottom-level, where marginalization and sex are employed.

The marginalization index is classified as follows, in decreasing order of severity: Very High (VH) (Chiapas, Guerrero and Oaxaca), High (H) (Campeche, Hidalgo, Michoacan, Puebla, San Luis Potosi, Veracruz and Yucatan), Medium (ME) (Durango, Guanajuato, Morelos, Nayarit, Quintana Roo, Sinaloa, Tabasco, Tlaxcala and Zacatecas), Low (L) (Aguascalientes, Baja California Sur, Chihuahua, Colima, Jalisco, Mexico, Queretaro, Sonora and Tamaulipas) and Very Low (VL) (Baja California, Ciudad de Mexico, Coahuila and Nuevo Leon). In this way, the number of time series at bottom-level is 10 ( $2 \times 5$ ), that is the levels of marginalization by two levels sex men (M) and woman (W) respectability. So, the total number of time series to forecast is 16 ( $10+5+1$ ).

To forecast the hierarchical time series, it is necessary to establish at least some restrictions, such as

$$(1) \quad \widehat{Y}_n(h) = \widehat{Y}_{VH,n}(h) + \widehat{Y}_{H,n}(h) + \widehat{Y}_{ME,n}(h) + \widehat{Y}_{L,n}(h) + \widehat{Y}_{VL,n}(h)$$

where

$$(2) \quad \widehat{Y}_{VH,n}(h) = \widehat{Y}_{VHM,n}(h) + \widehat{Y}_{VHW,n}(h)$$

$$(3) \quad \widehat{Y}_{H,n}(h) = \widehat{Y}_{HM,n}(h) + \widehat{Y}_{HW,n}(h)$$

$$(4) \quad \widehat{Y}_{ME,n}(h) = \widehat{Y}_{MEM,n}(h) + \widehat{Y}_{MEW,n}(h)$$

$$(5) \quad \widehat{Y}_{L,n}(h) = \widehat{Y}_{LM,n}(h) + \widehat{Y}_{LW,n}(h)$$

$$(6) \quad \widehat{Y}_{VL,n}(h) = \widehat{Y}_{VLM,n}(h) + \widehat{Y}_{VLW,n}(h)$$

and  $\widehat{Y}_{j,n}(h)$  is the vector of initial h-step forecast, made at time n for the time series  $j$ . In particular  $\widehat{Y}_n(h)$  is stacked in same order as  $Y_t$  (see below).

One possibility to forecast the hierarchical time series is to use ARIMA models or smoothing techniques. However, the sum of the respective forecasts may not add up. In other words, the above restrictions, that give coherent forecasts, can be unsatisfied. In matrix notation a generalization of (1) - (6) (Hyndman & Athanasopoulos, 2018), where, in addition the individual time series considered, can be written as

$$Y_t = \begin{bmatrix} Y_t \\ Y_{VH,t} \\ Y_{H,t} \\ Y_{ME,t} \\ Y_{L,t} \\ Y_{VL,t} \\ Y_{VHM,t} \\ Y_{VHW,t} \\ Y_{HM,t} \\ Y_{HW,t} \\ Y_{MEM,t} \\ Y_{MEW,t} \\ Y_{LM,t} \\ Y_{LW,t} \\ Y_{VLM,t} \\ Y_{VLW,t} \end{bmatrix} = \begin{bmatrix} 1111111111 \\ 1100000000 \\ 0011000000 \\ 0000110000 \\ 0000001100 \\ 0000000011 \\ I_{10} \\ S \end{bmatrix} \begin{bmatrix} Y_{VHM,t} \\ Y_{VHW,t} \\ Y_{HM,t} \\ Y_{HW,t} \\ Y_{MEM,t} \\ Y_{MEW,t} \\ Y_{LM,t} \\ Y_{LW,t} \\ Y_{VLM,t} \\ Y_{VLW,t} \end{bmatrix}$$

where  $I_{10}$  is the identity matrix of size 10x10. In hierarchical terms, let  $\check{Y}_n(h)$  be the forecast given by

$$\check{Y}_n(h) = \mathbf{SP}\widehat{Y}_n(h)$$

for some matrix  $\mathbf{P}$  that extract and combine base or bottom-level forecasts  $\widehat{Y}_n(h)$  and  $\mathbf{S}$  that adds them up. That is,  $\check{Y}_n(h)$  are the revised reconciled forecasts. There are three generic methods to estimate the forecast: bottom-up, top-down and middle-out. To obtain the best estimate, Generalized Least Squares is employed (Hyndman, Ahmed, Athanasopoulos, & Shang, 2011). It can be seen that the forecasts are aggregated consistently, unbiased and have minimum variance.

To choose the best forecasts the hts library (Hyndman, Lee, Wang, & Wickramasuriya, 2018) in R 4.0.1 is used (R Core Team, 2019), the forecasting methods ETS (Exponential Smoothing), ARIMA (Autoregressive Integrated Moving Average) and rw (Random walk) are explored. Forecasts are distributed in the hierarchy using optimal combination method (comb), bottom-up (bu), middle-out (mo), top-down (three methods: the two Gross-Sohl methods -tdgsa and tdgsf- and the forecast-proportion approach -tdfp-) (see Hyndman et al., 2011).

Finally, the statistical criteria giving forecast accuracy measures used are (Hyndman & Koehler, 2006): ME (Mean Error), RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), MPE (Mean Percentage Error) and MASE (Mean Absolute Scaled Error). Based on their mean at the bottom-level time series, the best forecast is chosen.

One limitation of these estimates is that the method does not generate prediction intervals. However, for our objective, the point forecasts are sufficient because we assume that propose an approach to establish a distribution of resource allocation objectively can be made based on this kind of previsions. The imposed forecast horizon is

$h = 13$ . Other limitation is the assumption that the marginalization level is the same for all the forecast horizon. The libraries used for R were: forecast (Hyndman et al., 2019; Hyndman & Khandakar, 2008), data.table (Dowle & Srinivasan 2019) and zoom (Barbu, 2013). The code is available upon request to the authors.

## Results

It is found that the best forecast was the obtained through ARIMA based on the mean of several statistical criteria at the bottom-level time series (see **Appendix**). We present results from our analysis in both tabular and graphical form. **Table 1** shows the observed and forecast numbers of death from Diabetes in each of the hierarchical levels of the forecast. To understand, it the column labeled Total is the entire expected deaths, the next five columns represent the second level of the hierarchy, based on level of marginalization (High, Low, Medium, Very High and Very Low). The next ten columns show the data by the combination of marginalization and sex, with the last character of the column label indicating if the forecast is for men (M) or women (W).

**Figure 3** and **Figure 4** show graphically the forecast for each level of the hierarchy used in the forecasting methodology. **Figure 3** (top) corresponds to the national level forecast of the Diabetes mortality rate. It clearly increases, following the prevailing trend in the country over the past years. **Figure 3** (bottom) shows the estimated Diabetes mortality rate for the second level of the hierarchy, based on the level of marginalization. Up until 2017, the highest level of Diabetes mortality was in areas of Very Low marginalization, suggesting that Diabetes is a disease of the affluent people in Mexico, which corresponds to work on Diabetes and obesity in the country (Sparks & Sparks, 2012); however, the gap between areas of High and Low marginalization was shrinking later in the observed

data. In the forecast, the areas of High (H) and Very High (VH) marginalization show the greatest increases in Diabetes mortality.

**Figure 4** presents the observed and forecast rates of mortality separately by marginalization level and sex. In the observed data prior to 2017, women faced a larger burden of mortality related to Diabetes than men (Flores et al., 2016), but again this gap has been shrinking in recent years. In the forecast, many of the ongoing trends in male versus female Diabetes mortality experience a cross over, where men begin to experience higher Diabetes mortality in some sub-areas of the country than women. Similar to what was shown in **Figure 3**, **Figure 4** shows that in areas of High and Very High marginalization, men show forecast rates of Diabetes mortality that cross over female rates and become higher over time.

According to **Table 2**, the hierarchical forecasts point that the appropriate distribution of the resource allocation should consider mainly the High and Low levels, given that they accumulate more than half of the future deaths by Diabetes in Mexico for the next years. In fact, in each one, the number of male deaths will be greater than female deaths for both levels. The maximum expected of deaths will be for male population at Low level. This scenario highlights the mentioned polarization in Mexico and it also suggest that a preventive health policy should be applied as soon as possible.

It is also important to recognize that the Medium and Very Low levels will jointly concentrate 1 of every 3 deaths from Diabetes in Mexico (see **Table 2**). It is also observed that the deaths per sex for both levels will be greater for male population. The smallest resource is required for the Very High level where the poverty and its consequences are their main characteristics. In other words, there is not a direct relationship among the marginalization and the expected percentage of deaths by Diabetes for the Mexican case.

## Conclusion

This analysis presents results of an analysis of hierarchical forecasts applied to the problem of distribution of resources to address the burden that Diabetes mortality is expected for Mexico by 2030. Overall, the forecasts estimated here show significant differences based on levels of marginalization and sex. Likewise, the gaps between men and women are notorious as well as between the levels of marginalization. Thereby, there is enough evidence that is not a good idea to consider a uniform distribution to face the economic burden caused by the Diabetes.

The hierarchical forecasts show that if the current trends continue, there will be a divergence by marginalization and sex in mortality in Mexico. Even worse, these forecasts indicate that the rates will increase the most simultaneously at high income level and some poor areas of the country. Through this statistical tool, it was possible to show not only the long-term trends in Diabetes mortality, but how the trends vary among areas of the country and by subpopulations.

The phenomenon presents notable differences by marginalization and sex; in fact, the increase in the mortality rate is clearly differentiated. This suggest that it could be necessary to implement preventive and specific health policies based on geographic region. It is also evident that the current preventive health policies need be rethought to reduce mortality from Diabetes in Mexico.

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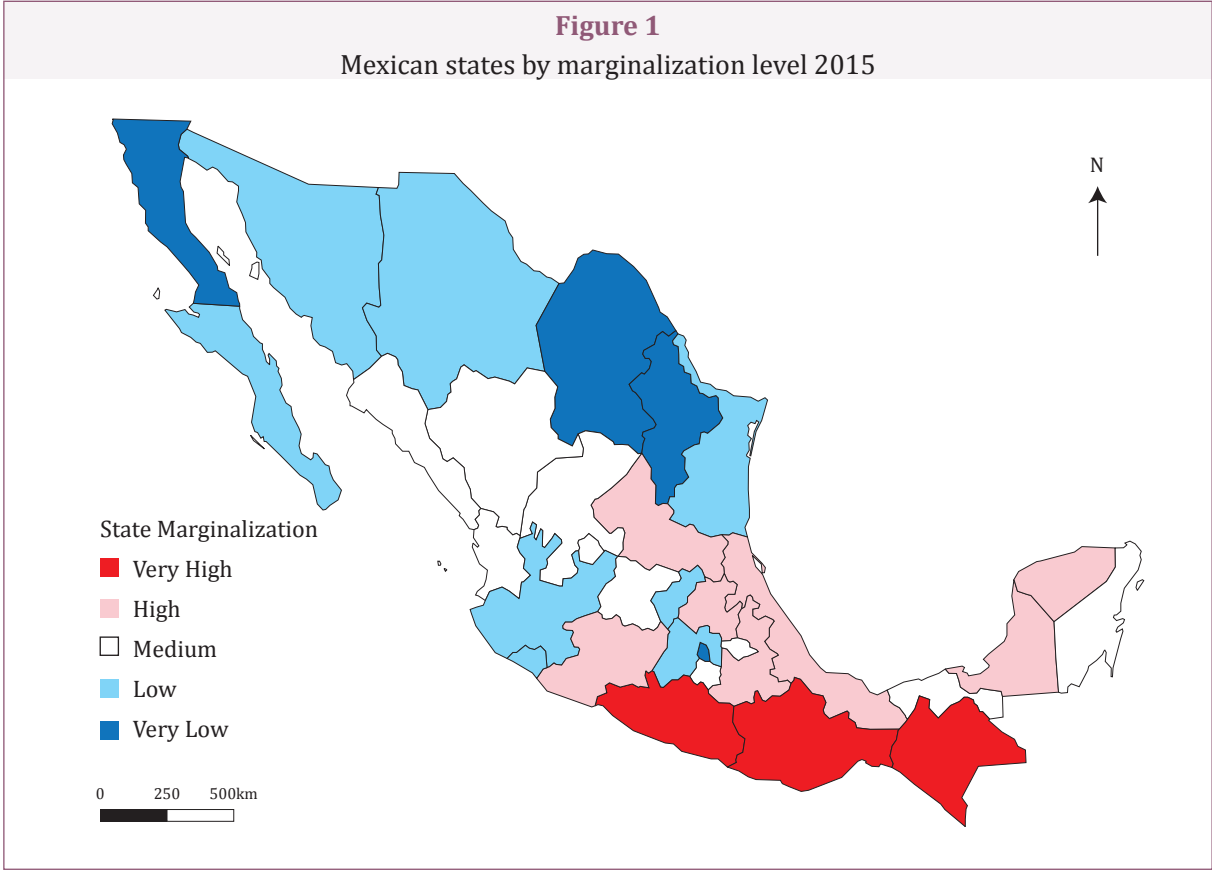
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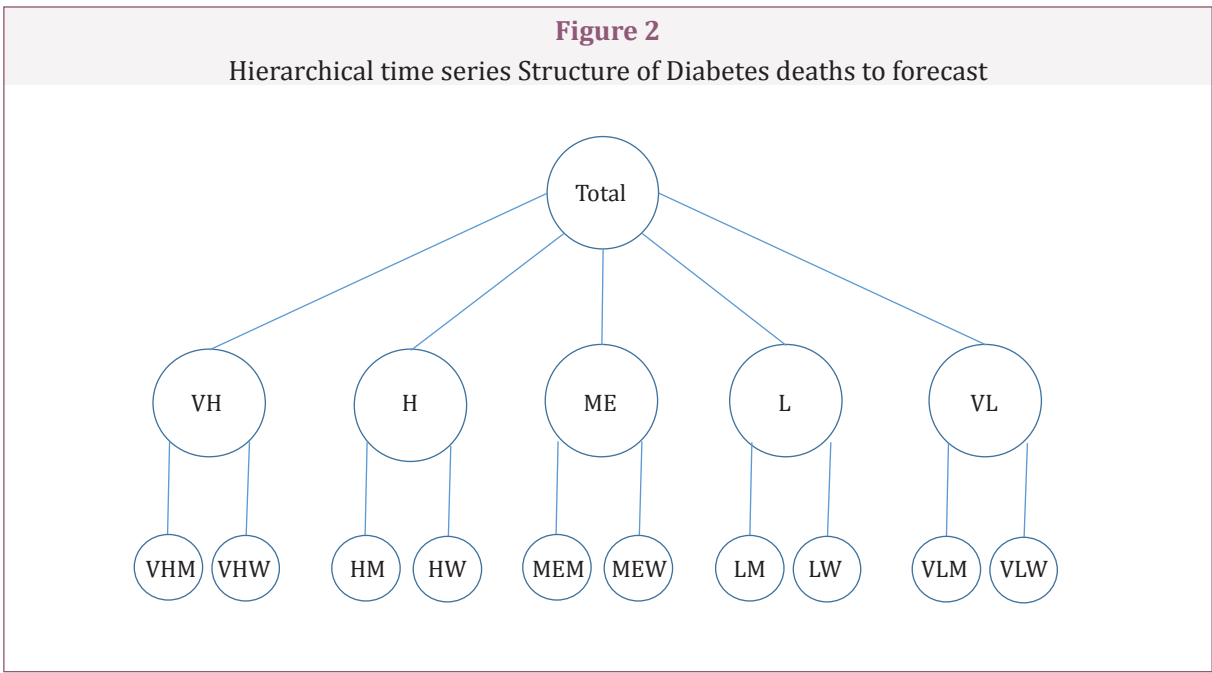


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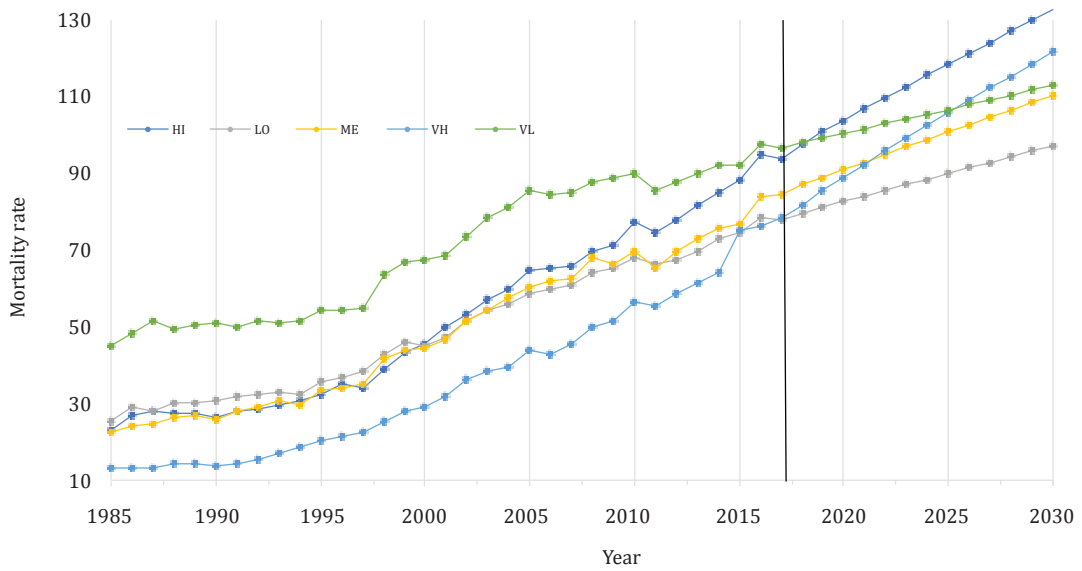
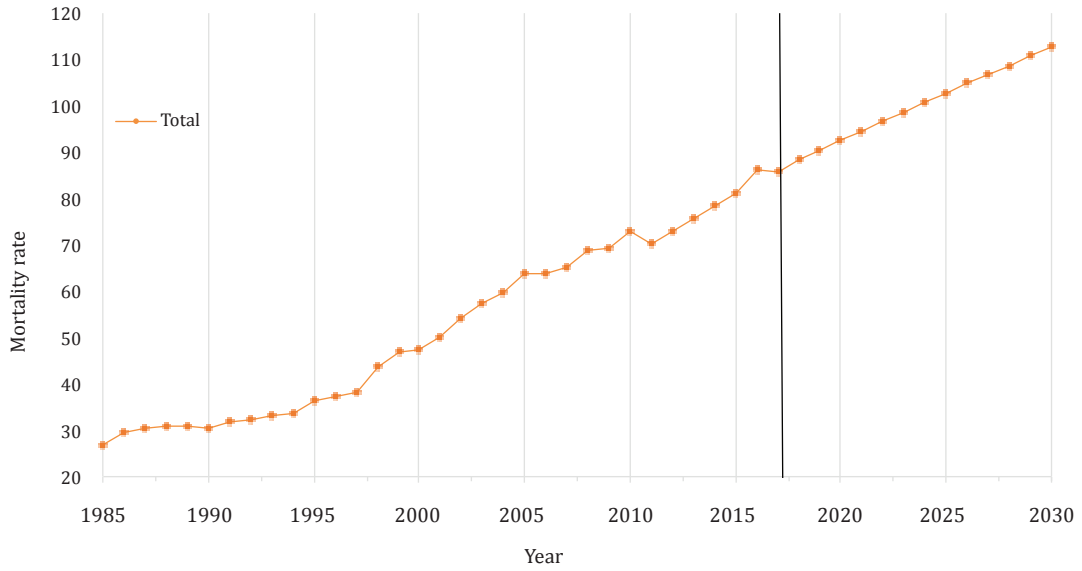




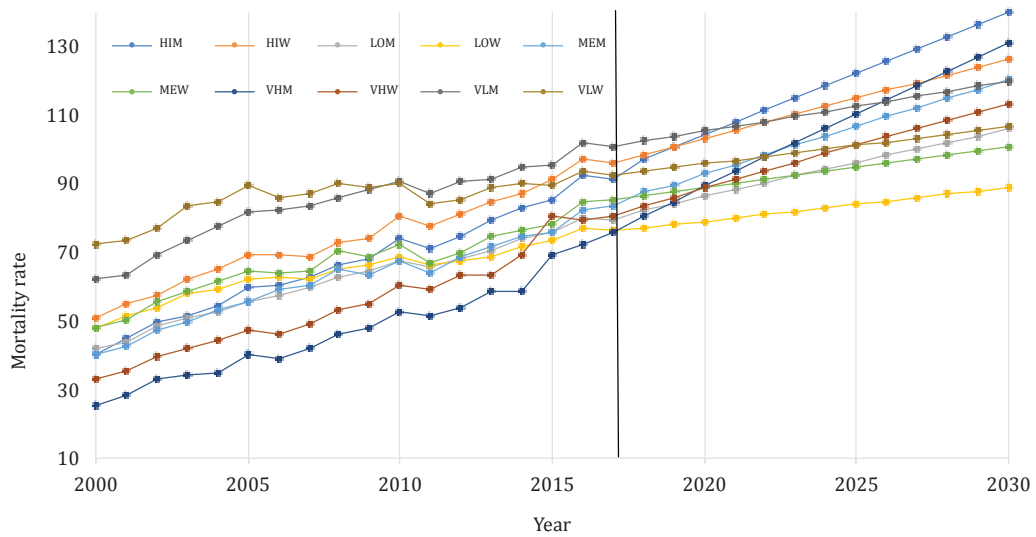
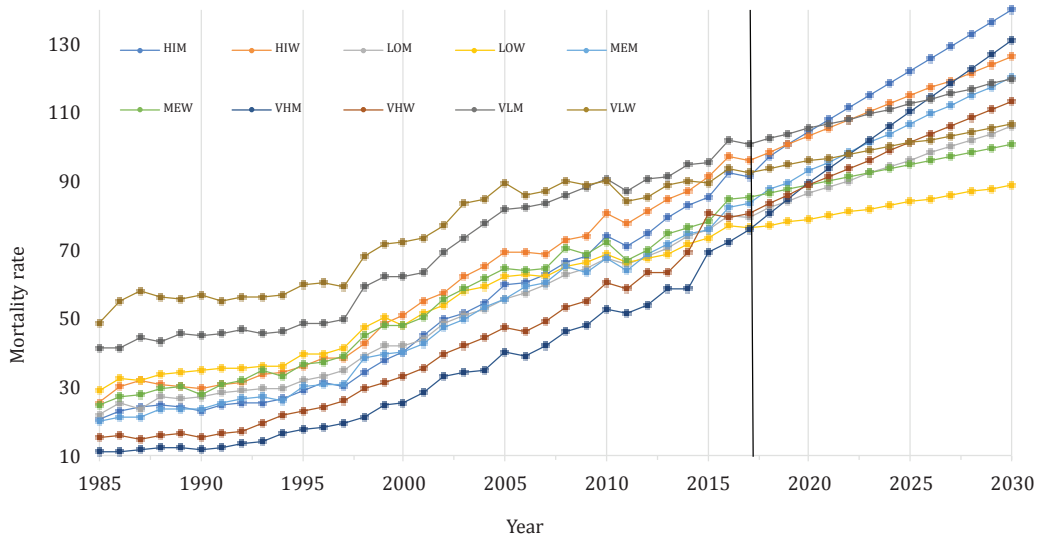
Source: Conapo (2015).



**Figure 3**  
Forecast of Diabetes mortality rate at the national level (top) and based on level of marginalization (bottom) to 2030



**Figure 4**  
Forecast of Diabetes mortality rate by marginalization and sex (top)  
and enlarged (bottom) to 2030



**Table 2**  
Percentage of deaths by marginalization and sex: Observed (1985-2017) and forecasted (2018-2030)

Year	Economic Burden distribution (%)																
	Total First level						Total Second level										
		HI	LO	ME	VH	VL		HIM	HIW	LOM	LOW	MEM	MEW	VHM	VHW	VLM	VLW
1985	100.00	20.87	27.72	13.56	5.11	32.73	100.00	9.18	11.70	11.89	15.83	6.01	7.56	2.17	2.94	14.69	18.04
1986	100.00	21.94	28.56	13.45	4.78	31.28	100.00	9.48	12.46	12.43	16.14	5.88	7.57	1.97	2.81	13.16	18.12
1987	100.00	22.68	27.11	13.41	4.66	32.15	100.00	9.71	12.97	11.52	15.59	5.76	7.65	2.04	2.62	13.71	18.44
1988	100.00	21.75	29.07	14.23	4.92	30.02	100.00	9.59	12.16	12.78	16.29	6.25	7.98	2.13	2.79	12.80	17.22
1989	100.00	21.37	29.16	14.38	5.04	30.06	100.00	9.44	11.93	12.64	16.52	6.30	8.08	2.13	2.91	13.26	16.80
1990	100.00	20.79	29.99	14.06	4.85	30.32	100.00	8.91	11.87	12.98	17.01	6.38	7.67	2.05	2.80	13.14	17.18
1991	100.00	21.28	30.11	14.78	4.99	28.83	100.00	9.36	11.92	13.28	16.84	6.65	8.14	2.12	2.88	12.79	16.04
1992	100.00	21.16	30.02	15.02	5.08	28.72	100.00	9.29	11.87	13.36	16.65	6.72	8.30	2.22	2.86	12.82	15.89
1993	100.00	21.35	29.97	15.56	5.50	27.62	100.00	9.11	12.24	13.24	16.73	6.74	8.82	2.31	3.19	12.12	15.51
1994	100.00	21.93	29.67	14.71	6.08	27.61	100.00	9.39	12.53	13.23	16.44	6.41	8.30	2.59	3.49	12.18	15.43
1995	100.00	21.55	30.41	15.37	5.97	26.70	100.00	9.46	12.09	13.47	16.94	6.84	8.53	2.58	3.39	11.68	15.01
1996	100.00	22.39	30.22	15.29	6.09	26.00	100.00	9.92	12.48	13.63	16.59	6.84	8.45	2.61	3.49	11.35	14.65
1997	100.00	21.43	31.28	15.40	6.41	25.47	100.00	9.16	12.27	14.11	17.18	6.71	8.70	2.72	3.69	11.39	14.09
1998	100.00	21.09	30.78	16.01	6.29	25.83	100.00	9.20	11.89	13.72	17.06	7.22	8.79	2.59	3.70	11.76	14.07
1999	100.00	21.75	31.00	15.60	6.43	25.22	100.00	9.31	12.44	13.92	17.08	6.91	8.69	2.77	3.66	11.49	13.73
2000	100.00	22.66	30.00	15.61	6.62	25.10	100.00	9.74	12.92	13.81	16.20	6.98	8.63	2.82	3.81	11.40	13.71
2001	100.00	23.49	30.09	15.48	6.81	24.13	100.00	10.25	13.23	13.64	16.44	6.95	8.54	2.95	3.86	10.97	13.16
2002	100.00	23.08	30.08	15.84	7.19	23.80	100.00	10.42	12.67	14.07	16.01	7.11	8.73	3.20	3.99	11.07	12.73
2003	100.00	23.10	30.16	15.63	7.07	24.04	100.00	10.16	12.93	13.93	16.23	7.01	8.62	3.10	3.97	11.05	12.99
2004	100.00	23.32	29.79	15.94	7.06	23.90	100.00	10.31	13.01	13.83	15.96	7.23	8.71	3.03	4.03	11.22	12.68
2005	100.00	23.61	29.63	15.70	7.33	23.74	100.00	10.59	13.02	13.81	15.82	7.14	8.56	3.28	4.05	11.17	12.57
2006	100.00	23.57	30.05	16.08	7.10	23.20	100.00	10.61	12.96	14.13	15.92	7.55	8.53	3.17	3.93	11.17	12.03
2007	100.00	23.37	30.12	16.05	7.48	22.99	100.00	10.76	12.61	14.51	15.61	7.57	8.48	3.36	4.12	11.05	11.94
2008	100.00	23.42	29.96	16.59	7.72	22.32	100.00	10.77	12.65	14.43	15.53	7.82	8.78	3.48	4.24	10.71	11.61
2009	100.00	23.61	30.23	16.04	7.93	22.19	100.00	10.94	12.67	14.67	15.56	7.56	8.48	3.59	4.34	10.86	11.33
2010	100.00	24.29	30.03	16.11	8.25	21.32	100.00	11.28	13.01	14.69	15.33	7.63	8.47	3.73	4.52	10.51	10.82
2011	100.00	24.37	30.43	15.78	8.42	21.00	100.00	11.33	13.04	14.89	15.54	7.59	8.20	3.82	4.60	10.48	10.52
2012	100.00	24.56	29.98	16.14	8.59	20.73	100.00	11.43	13.13	14.84	15.15	7.87	8.27	3.82	4.76	10.51	10.21
2013	100.00	24.88	29.68	16.42	8.62	20.39	100.00	11.67	13.21	14.78	14.91	7.92	8.51	4.02	4.61	10.11	10.28
2014	100.00	24.86	29.98	16.39	8.71	20.06	100.00	11.78	13.08	14.96	15.02	7.96	8.43	3.86	4.84	10.12	9.95
2015	100.00	24.92	29.75	16.16	9.83	19.33	100.00	11.69	13.24	14.86	14.90	7.82	8.34	4.41	5.43	9.76	9.57
2016	100.00	25.27	29.52	16.60	9.37	19.24	100.00	11.95	13.32	14.84	14.68	8.04	8.56	4.33	5.04	9.83	9.41
2017	100.00	25.06	29.38	16.81	9.68	19.06	100.00	11.85	13.21	14.76	14.62	8.19	8.63	4.54	5.14	9.76	9.30
2018	100.00	25.34	29.29	16.84	9.83	18.70	100.00	12.22	13.13	14.89	14.40	8.34	8.50	4.68	5.15	9.59	9.11
2019	100.00	25.50	29.20	16.81	10.01	18.47	100.00	12.38	13.13	14.93	14.27	8.37	8.44	4.82	5.19	9.48	8.99
2020	100.00	25.63	29.10	16.85	10.17	18.24	100.00	12.52	13.11	14.96	14.14	8.48	8.37	4.95	5.22	9.37	8.87
2021	100.00	25.76	29.02	16.86	10.33	18.03	100.00	12.65	13.10	15.00	14.02	8.54	8.31	5.08	5.26	9.28	8.75
2022	100.00	25.88	28.94	16.88	10.48	17.83	100.00	12.78	13.09	15.03	13.91	8.62	8.25	5.19	5.28	9.18	8.65
2023	100.00	25.99	28.86	16.89	10.62	17.64	100.00	12.90	13.09	15.06	13.81	8.69	8.20	5.30	5.31	9.10	8.55
2024	100.00	26.09	28.79	16.90	10.75	17.47	100.00	13.01	13.08	15.08	13.71	8.75	8.15	5.41	5.34	9.01	8.45
2025	100.00	26.19	28.72	16.91	10.87	17.30	100.00	13.12	13.07	15.11	13.61	8.81	8.10	5.50	5.37	8.94	8.36
2026	100.00	26.29	28.66	16.92	10.99	17.14	100.00	13.22	13.07	15.13	13.53	8.87	8.05	5.60	5.39	8.86	8.28
2027	100.00	26.38	28.60	16.93	11.10	16.99	100.00	13.32	13.06	15.16	13.44	8.92	8.01	5.68	5.41	8.79	8.20
2028	100.00	26.46	28.54	16.95	11.20	16.85	100.00	13.41	13.05	15.18	13.36	8.98	7.97	5.77	5.43	8.73	8.12
2029	100.00	26.54	28.48	16.95	11.30	16.71	100.00	13.50	13.05	15.20	13.29	9.02	7.93	5.85	5.46	8.66	8.05
2030	100.00	26.62	28.43	16.96	11.40	16.59	100.00	13.58	13.04	15.22	13.21	9.07	7.89	5.92	5.47	8.60	7.98

## Appendix

**Table A1**  
Accurate statistics by forecast method and hierarchical perspective for individual series

Time Series											
Statistics	HIM	HIW	LOM	LOW	MEM	MEW	VHM	VHW	VLM	VLW	Mean
ETS, comb											
ME	37.7280	20.9346	52.1806	7.0980	38.8140	44.3801	29.0629	23.8024	29.0113	-12.3165	27.0695
RMSE	263.0375	314.9066	287.3520	291.1597	188.0735	238.1917	123.2657	159.0585	231.4569	267.1759	236.3678
MAE	210.4737	242.9141	230.2858	243.6743	137.5848	177.2446	80.7564	100.1290	171.3872	209.2680	180.3718
MAPE	4.1668	3.5896	3.3616	3.2021	3.5449	3.8632	4.3238	4.0088	2.9432	3.4557	3.6460
MPE	0.5617	0.1644	0.7385	-0.4666	0.7515	0.6808	1.5426	1.2997	0.4383	-0.6069	0.5104
MASE	0.5737	0.6297	0.5344	0.5935	0.5465	0.6366	0.5743	0.6250	0.6705	0.8239	0.6208
ARIMA, comb											
ME	35.1087	39.0870	55.5419	8.5916	48.9606	6.8383	35.4474	38.1102	0.6655	0.8089	26.9160
RMSE	255.3413	297.8797	270.8985	300.3741	182.9644	232.6668	124.6221	155.5576	235.7998	259.4100	231.5514
MAE	211.8437	232.8921	204.3192	248.1299	135.8920	172.0523	80.9180	102.7285	185.9218	193.3167	176.8014
MAPE	4.2070	3.4570	2.9708	3.2492	3.6458	3.9463	4.1979	4.1838	3.3392	3.0002	3.6197
MPE	0.3659	0.2072	0.6667	-0.4430	1.2207	-0.8101	1.8972	1.7926	-0.6429	-0.1264	0.4128
MASE	0.5774	0.6037	0.4742	0.6044	0.5398	0.6180	0.5754	0.6412	0.7273	0.7611	0.6122
RW, comb											
ME	334.9375	364.2188	414.4688	384.6250	233.5625	238.3438	137.0625	151.9063	230.5000	193.8750	268.3500
RMSE	448.3285	476.3709	507.0032	488.9572	317.4291	336.7042	200.5305	223.0612	331.8646	326.3546	365.6604
MAE	366.8750	385.7813	430.9063	410.5625	251.7500	278.4063	140.6250	160.2188	255.6250	254.0000	293.4750
MAPE	6.4502	5.6048	5.8927	5.0026	6.2288	6.2597	7.3851	7.1162	4.1920	3.8217	5.7954
MPE	5.6667	5.2956	5.5798	4.7142	5.8203	5.3017	7.0772	6.5489	3.7268	2.9557	5.2687
MASE	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
ETS, bu											
ME	37.5357	20.6606	45.9435	-0.1015	39.3016	45.1547	29.9351	25.2182	31.0995	-9.6158	26.5131
RMSE	261.3285	311.9974	275.7980	296.3138	188.4151	237.4663	123.4239	157.2529	235.4252	267.7355	235.5157
MAE	209.8246	241.2964	219.1647	249.9734	137.2041	175.8403	81.0389	99.1561	173.0626	209.6145	179.6175
MAPE	4.1571	3.5724	3.1802	3.3696	3.5165	3.8186	4.3042	3.9854	2.9542	3.4182	3.6277
MPE	0.5439	0.1453	0.4835	-0.6908	0.7746	0.7098	1.5627	1.3263	0.5827	-0.4759	0.4962
MASE	0.5719	0.6255	0.5086	0.6089	0.5450	0.6316	0.5763	0.6189	0.6770	0.8253	0.6189
ARIMA, bu											
ME	37.2668	42.1604	48.7640	0.0863	44.8959	0.0395	35.2197	37.7325	0.0839	0.1057	24.6355
RMSE	252.5123	301.3408	265.3871	297.2897	181.0829	234.1966	122.0932	157.2513	235.1100	258.5183	230.4782
MAE	207.2960	232.6407	201.9412	250.1241	135.0178	172.4941	78.5704	103.4700	186.1748	193.2875	176.1017
MAPE	4.0760	3.3826	2.9047	3.3366	3.6178	4.0923	4.1268	4.1772	3.3553	3.0087	3.6078
MPE	0.3722	0.2185	0.4822	-0.6259	0.9484	-1.1655	1.8402	1.7232	-0.6631	-0.1451	0.2985
MASE	0.5650	0.6030	0.4686	0.6092	0.5363	0.6196	0.5587	0.6458	0.7283	0.7610	0.6096
RW, bu											
ME	334.9375	364.2188	414.4688	384.6250	233.5625	238.3438	137.0625	151.9063	230.5000	193.8750	268.3500
RMSE	448.3285	476.3709	507.0032	488.9572	317.4291	336.7042	200.5305	223.0612	331.8646	326.3546	365.6604
MAE	366.8750	385.7813	430.9063	410.5625	251.7500	278.4063	140.6250	160.2188	255.6250	254.0000	293.4750
MAPE	6.4502	5.6048	5.8927	5.0026	6.2288	6.2597	7.3851	7.1162	4.1920	3.8217	5.7954
MPE	5.6667	5.2956	5.5798	4.7142	5.8203	5.3017	7.0772	6.5489	3.7268	2.9557	5.2687
MASE	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Note: ETS (Exponential Smoothing), ARIMA (Autoregressive Integrated Moving Average), rw (Random walk), comb (optimal combination method), bu (bottom-up), mo (middle-out), tdgsa and tdgsf (Gross-Sohl methods top-down) and tdfp (forecast-proportion top-down approach).

Time Series											
Statistics	HIM	HIW	LOM	LOW	MEM	MEW	VHM	VHW	VLM	VLW	Mean
ETS, mo											
ME	37.1645	20.0731	60.5508	23.1506	37.1676	42.4592	26.9522	21.4561	26.8075	-20.0193	27.5762
RMSE	267.6493	322.9059	311.2819	293.7698	188.1703	237.3293	123.4091	161.8518	229.6268	276.9614	241.2955
MAE	211.5615	249.6546	250.5701	235.5260	138.2907	176.3267	80.1206	101.9027	171.7625	222.5084	183.8224
MAPE	4.1236	3.7094	3.7228	2.9759	3.5728	3.8337	4.3057	4.0181	2.9792	3.7091	3.6950
MPE	0.5301	0.1265	1.1146	-0.0104	0.6422	0.5774	1.4265	1.1873	0.1819	-0.8945	0.4882
MASE	0.5767	0.6471	0.5815	0.5737	0.5493	0.6333	0.5697	0.6360	0.6719	0.8760	0.6315
ARIMA, mo											
ME	28.2180	31.9275	65.9611	23.2750	56.7039	16.6656	35.1854	38.2809	0.0839	0.1057	29.6407
RMSE	263.8437	292.8569	282.7252	307.8060	189.9409	232.0011	130.9082	153.5401	235.1100	258.5183	234.7250
MAE	222.3334	230.4395	210.5765	251.2278	140.0138	171.5694	86.3714	100.4632	186.1748	193.2875	179.2457
MAPE	4.4595	3.5475	3.1301	3.2156	3.8157	3.7694	4.3394	4.1116	3.3553	3.0087	3.6753
MPE	0.2404	0.1032	0.9441	-0.1451	1.7571	-0.3097	1.9073	1.8110	-0.6631	-0.1451	0.5500
MASE	0.6060	0.5973	0.4887	0.6119	0.5562	0.6163	0.6142	0.6270	0.7283	0.7610	0.6207
RW, mo											
ME	334.9375	364.2188	414.4688	384.6250	233.5625	238.3438	137.0625	151.9063	230.5000	193.8750	268.3500
RMSE	448.3285	476.3709	507.0032	488.9572	317.4291	336.7042	200.5305	223.0612	331.8646	326.3546	365.6604
MAE	366.8750	385.7813	430.9063	410.5625	251.7500	278.4063	140.6250	160.2188	255.6250	254.0000	293.4750
MAPE	6.4502	5.6048	5.8927	5.0026	6.2288	6.2597	7.3851	7.1162	4.1920	3.8217	5.7954
MPE	5.6667	5.2956	5.5798	4.7142	5.8203	5.3017	7.0772	6.5489	3.7268	2.9557	5.2687
MASE	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
ETS, tdgsa											
ME	275.5167	141.6664	250.0393	-115.4341	186.1718	66.5740	206.8873	208.6223	-256.0069	-665.8175	29.8219
RMSE	761.9894	402.9312	630.7999	585.7394	475.8387	241.5756	566.1257	560.7515	719.5201	1774.3676	671.9639
MAE	501.1943	285.8825	453.9422	420.8711	336.5558	198.6868	377.5481	372.4879	549.7590	1331.7306	482.8658
MAPE	7.8631	4.1187	6.1334	4.7679	8.5177	5.1145	22.1688	17.4824	8.8026	18.3863	10.3355
MPE	-0.3781	0.2999	-0.0091	0.2249	-0.4608	0.2118	-5.8654	-3.7036	-0.5187	-3.7119	-1.3911
MASE	1.3661	0.7410	1.0535	1.0251	1.3369	0.7137	2.6848	2.3249	2.1506	5.2430	1.8640
ARIMA, tdgsa											
ME	279.1943	146.1993	254.9955	-109.6870	188.7125	69.5835	207.9697	209.9981	-251.8725	-660.9766	33.4117
RMSE	747.6509	396.0418	619.4915	612.0923	472.9785	254.1954	561.8917	555.6817	734.6556	1787.8297	674.2509
MAE	516.3520	300.0356	463.6866	436.6220	342.3574	196.0412	379.6023	378.5918	526.4393	1299.9160	483.9644
MAPE	8.3415	4.2700	6.4776	4.7261	8.8917	5.1716	22.5948	18.1198	8.2482	17.8265	10.4668
MPE	-0.3952	0.2986	-0.0443	0.2066	-0.5187	0.1829	-5.9856	-3.8234	-0.5254	-3.6850	-1.4289
MASE	1.4074	0.7777	1.0761	1.0635	1.3599	0.7042	2.6994	2.3630	2.0594	5.1178	1.8628
RW, tdgsa											
ME	534.3479	452.0581	598.1072	262.4844	366.9778	273.1297	290.4123	311.8705	-10.6198	-395.2680	268.3500
RMSE	931.8876	626.9853	872.8975	582.1246	601.3943	377.1402	617.9916	625.4077	604.8573	1617.5420	745.8228
MAE	636.6406	474.8413	661.7605	468.2631	432.3602	313.5352	412.8759	426.8633	468.6928	1241.0736	553.6906
MAPE	8.2768	5.8092	7.1233	6.2025	8.7725	6.4197	20.7062	17.1214	8.3658	17.7603	10.6558
MPE	4.5459	5.0764	5.0510	4.7656	4.6696	5.0906	0.0657	1.8801	3.2879	-0.0321	3.4401
MASE	1.7353	1.2309	1.5357	1.1405	1.7174	1.1262	2.9360	2.6643	1.8335	4.8861	2.0806

Note: ETS (Exponential Smoothing), ARIMA (Autoregressive Integrated Moving Average), rw (Random walk), comb (optimal combination method), bu (bottom-up), mo (middle-out), tdgsa and tdgsf (Gross-Sohl methods top-down) and tdfp (forecast-proportion top-down approach).



Time Series											
Statistics	HIM	HIW	LOM	LOW	MEM	MEW	VHM	VHW	VLM	VLW	Mean
ETS, tdgsf											
ME	31.8729	38.2180	42.3003	46.8638	21.9968	25.2257	10.0593	12.4935	32.7809	36.4082	29.8219
RMSE	611.4952	348.3501	502.6745	519.8036	370.2743	228.8135	441.2936	436.7877	543.0443	1316.0607	531.8597
MAE	465.2538	250.0464	389.5916	385.5247	293.2781	190.4671	344.2115	331.3603	437.0435	1121.2255	420.8003
MAPE	9.2470	3.9456	6.3044	4.8805	9.2010	5.0788	27.4402	20.6450	8.4517	17.8489	11.3043
MPE	-4.7188	-1.1853	-2.7452	2.0641	-4.6981	-0.6831	-18.4311	-13.3528	4.0642	6.1080	-3.3578
MASE	1.2682	0.6482	0.9041	0.9390	1.1650	0.6841	2.4477	2.0682	1.7097	4.4143	1.6248
ARIMA, tdgsf											
ME	35.7095	42.8184	47.3920	52.5049	24.6446	28.2622	11.2702	13.9973	36.7268	40.7907	33.4117
RMSE	592.0496	339.6220	487.0588	549.5315	365.9135	241.9874	434.9571	429.3455	562.9431	1333.4672	533.6876
MAE	457.6052	275.8887	388.2488	409.9439	292.5223	188.7163	335.8340	321.0625	440.7904	1134.2067	424.4819
MAPE	9.3461	4.3841	6.5111	4.9074	9.4473	5.1649	27.4003	20.5980	8.3302	17.9397	11.4029
MPE	-4.7367	-1.1866	-2.7814	2.0461	-4.7584	-0.7123	-18.5655	-13.4838	4.0579	6.1324	-3.3988
MASE	1.2473	0.7151	0.9010	0.9985	1.1620	0.6778	2.3882	2.0039	1.7244	4.4654	1.6284
RW, tdgsf											
ME	296.4418	351.0459	395.2603	420.9602	206.6690	232.7552	98.2195	120.3605	271.3672	290.4205	268.3500
RMSE	724.0261	530.8234	678.2329	634.3233	456.4934	342.9909	470.5942	473.6675	557.3712	1288.7213	615.7244
MAE	502.2276	397.5933	506.9187	525.6359	332.6845	281.6424	341.1810	331.1626	501.2453	1143.7272	486.4018
MAPE	7.6478	4.9877	5.9036	7.2455	7.9651	5.8607	23.5224	17.5450	10.0814	18.5800	10.9339
MPE	0.4181	3.6624	2.4533	6.5211	0.6487	4.2395	-11.7960	-7.2496	7.6972	9.4394	1.6034
MASE	1.3689	1.0306	1.1764	1.2803	1.3215	1.0116	2.4262	2.0669	1.9609	4.5029	1.8146
ETS, tdfp											
ME	39.3703	23.2284	62.0201	26.7724	38.3127	43.3736	27.3562	21.9250	30.2254	-14.3647	29.8219
RMSE	270.6147	318.5305	343.6103	306.2313	188.6614	248.8523	123.9756	163.0204	223.5041	255.3214	244.2322
MAE	218.3813	247.5655	286.9094	241.8558	140.2955	189.8175	80.2305	101.2012	176.7088	206.8442	188.9810
MAPE	4.3596	3.6548	4.2403	2.9599	3.7413	4.2463	4.5456	4.1594	3.0882	3.4444	3.8440
MPE	0.7041	0.3148	1.2645	0.1697	0.8160	0.7337	1.5863	1.3566	0.3643	-0.7032	0.6607
MASE	0.5952	0.6417	0.6658	0.5891	0.5573	0.6818	0.5705	0.6316	0.6913	0.8143	0.6439
ARIMA, tdfp											
ME	31.8071	36.4986	70.3861	29.7926	58.9079	19.7280	35.7390	39.0220	5.1623	7.0731	33.4117
RMSE	260.2963	303.4112	306.0749	335.2375	199.1667	244.2644	130.7689	158.0069	250.6704	274.7725	246.2670
MAE	215.7857	239.3780	231.3405	265.0061	147.0085	179.3341	86.5814	106.7968	186.5863	207.5034	186.5321
MAPE	4.3941	3.6336	3.3753	3.3224	3.9653	3.9211	4.3648	4.4058	3.2700	3.1147	3.7767
MPE	0.4081	0.2632	1.0890	0.0026	1.9020	-0.1570	2.0692	1.9577	-0.5096	0.0108	0.7036
MASE	0.5882	0.6205	0.5369	0.6455	0.5839	0.6441	0.6157	0.6666	0.7299	0.8169	0.6448
RW, tdfp											
ME	334.9375	364.2188	414.4688	384.6250	233.5625	238.3438	137.0625	151.9063	230.5000	193.8750	268.3500
RMSE	448.3285	476.3709	507.0032	488.9572	317.4291	336.7042	200.5305	223.0612	331.8646	326.3546	365.6604
MAE	366.8750	385.7813	430.9063	410.5625	251.7500	278.4063	140.6250	160.2188	255.6250	254.0000	293.4750
MAPE	6.4502	5.6048	5.8927	5.0026	6.2288	6.2597	7.3851	7.1162	4.1920	3.8217	5.7954
MPE	5.6667	5.2956	5.5798	4.7142	5.8203	5.3017	7.0772	6.5489	3.7268	2.9557	5.2687
MASE	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Note: ETS (Exponential Smoothing), ARIMA (Autoregressive Integrated Moving Average), rw (Random walk), comb (optimal combination method), bu (bottom-up), mo (middle-out), tdgsa and tdgsf (Gross-Sohl methods top-down) and tdfp (forecast-proportion top-down approach).