

Evaluating A Markov Regime-switching Model of Health Care Expenditure Dynamics *

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Abstract

This paper replicates and evaluates a Markov regime-switching approach to estimating the dynamic process of health care expenditure proposed by [Evans et al. \(2014\)](#). Our data includes the recorded monthly health expenditure of 99,965 individuals for 24-month period. The model assumes five distinct health-care-consumption states, among which two are zero-expenditure states and the rest of three are positive-expenditure states. The model also assumes that the proportion of the given population in those five health states is a ergodic dynamical system. We use GMM to estimate the Markov model parameters and have successfully matched target moments. We then label each string of consecutive positive health spending as one of the three positive-expenditure states. We examine the labeled positive-expenditure spells empirically and suggest an alternative labeling scheme to better characterize each health-care-consumption state.

keywords: heathcare, markov chain, regime-switching model,

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1 Introduction

[Evans, Humpherys and Taylor \(2014\)](#) offers a Markov regime-switching model for estimating and simulating monthly health care expenditures of individuals given their current health state. [Evans et al. \(2014\)](#) contrasts their Markov model to the stochastic variance model of [French and Jones \(2004\)](#), which models the process for log health costs as “the sum of a white noise process and a highly persistent AR(1) process” with catastrophic health cost shocks. The Markov regime-switch approach to health expenditures, [Evans et al. \(2014\)](#) argues, has at least two following advantages. First, it better accounts for the prevalence zero-expenditure periods. Second, the Markov process is more appealing on the intuitive level as it allows for clear distinction between different health states wherein “healthy” state is subdivided into two categories and “unhealthy” into three.

In this paper, we replicate the Markov regime-switching model for estimating health care costs by [Evans et al. \(2014\)](#) to validate and evaluate the effectiveness of the model. We use the same data used by the original study but with minor adjustment. We follow the steps provided by the original study to estimate the health care expenditure process. Moreover, we consider extra dimensions of gender and age, which are mostly disregarded in the original study, to enrich our understanding of the characteristics of distinct health expenditure categories. Our examination illustrates that gender and age can provide additional information about different types of positive health expenditure. We further suggest that the labels for health care expenditure types in [Evans et al. \(2014\)](#) may not fully capture the key features of some positive expenditure types, and would like to propose an alternative labeling scheme.

The structure of the rest of this paper is as follows. [Section 2](#) describes the data used to estimate the model. [Section 3](#) describes the Markov model used in this paper. [Section 4](#) consists of two parts. [Part 4.1](#) describes the GMM estimation procedure used to estimate model parameters and to present the estimation results. [Part 4.2](#) describes and discusses the process of identifying positive health expenditure types.

Section 5 provides a brief conclusion of this paper.

2 Data

We estimate the parameters of our model using a panel of total monthly health care expenditures for the same 24-month periods from a random sample of 99,965 individuals residing in the same U.S. city. In addition to their health expenditures, we would also include individual characteristics, such as age and gender, into our analysis.¹ Our data set consists of a subset of the monthly health care expenditures data used in [Evans et al. \(2014\)](#), with minor adjustments to prevent identifications of the individuals as well as the insurer. Following [Evans et al. \(2014\)](#), we assume a low degree of elasticity in the demand for health care, which provides a justification for using the health care expenditures as a proxy to predict actual health status.

Table 1: Descriptive statistics of the monthly health care expenditures

		Count	Mean	Median	Max	Min	St. Dev.
Expenditure	Total	2,399,160	305.31	0.0	422,855.84	0.0	2,235.93
	Zero	1,375,975	-	-	-	-	-
	Positive	1,023,185	715.88	173.30	422,855.84	0.01	3,380.62
	Female	1,228,872	328.18	0.0	355,495.02	0.0	2,008.85
	Male	1,170,288	281.29	0.0	422,855.84	0.0	2,451.61
Age	total	99,965	33.20	36	95	0	18.45
	Female	51,203	33.30	36	94	0	18.18
	Male	48,762	33.09	36	95	0	18.73

Table 1 provides a detailed descriptive statistics of our data. As in [Evans et al. \(2014\)](#), the most outstanding characteristic of the data is that more than half of our total observations (57.35%) have zero expenditures. As [Evans et al. \(2014\)](#) points out, such prevalence of zero-expenditure months poses a challenge to estimate monthly spending with a stochastic variance model. Figure 1 is a histogram that

¹Original data set included approximately 102,000 individuals and thus around 240,000 total recorded monthly health expenditures, among which 37 individuals have negative monthly health expenditures. As in [Evans et al. \(2014\)](#), we excluded 35 individuals from our truncated data set with negative monthly expenditures and only used the remaining for the estimation of our model.

provides more details about the distribution of the zero-expenditure months. For example, over one-eighth of all individuals, which constitute the largest group of all, have spent nothing for the entire span of 24 months. On the other hand, the second largest group, which accounts for nearly 8% of all individuals, consists of those with positive expenditures during the entire 24-months period. The rest of the groups takes between 2% and 5% of the entire sample.

Figure 1: Histogram of the fraction of individuals with a given number of zero-expenditure months

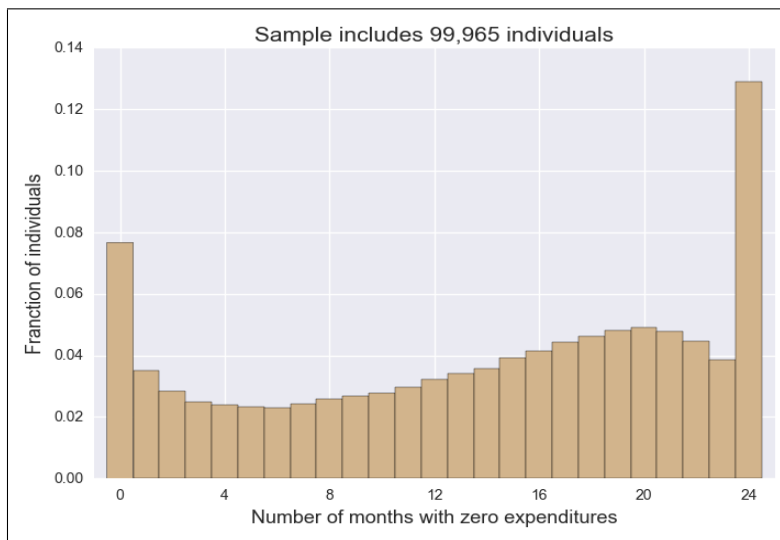


Figure 2 illustrates the mean and the standard deviation of positive health care expenditures by month. Although the mean of all positive monthly expenditure shows little change over the 24-month period, the standard deviation varies much more noticeable from one month to another. Perhaps the more informative is Figure 3, which shows the mean and the standard deviation of individuals by number of months when they have positive health care spending. There is a positive correlation between the number of positive-expenditure months and averaged monthly expenditures. In other words, people who commit to monthly health care frequently would typically have greater health care expenditures per month on average.

Gender is almost equally divided between female (51.2%) and male (48.8%) in our

Figure 2: Mean and standard deviation of positive monthly expenditures by month

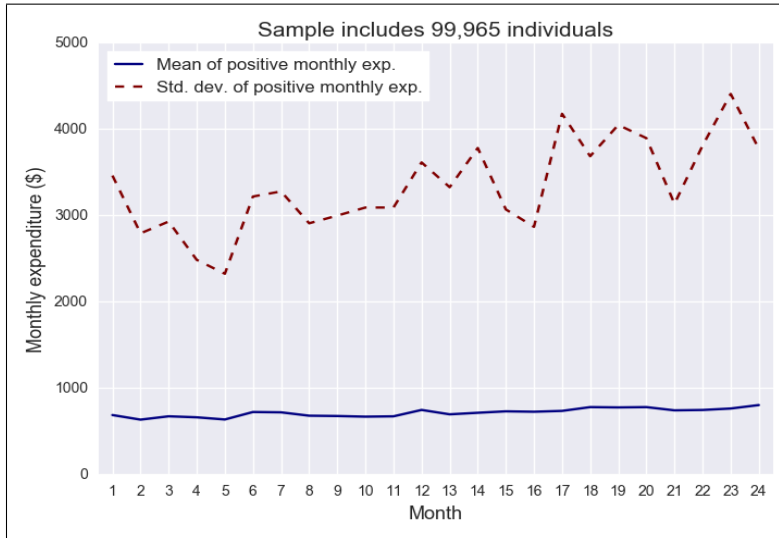
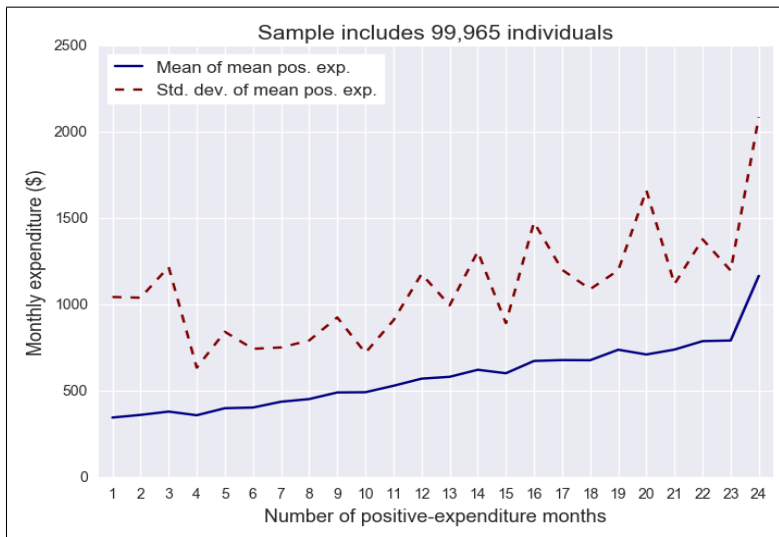
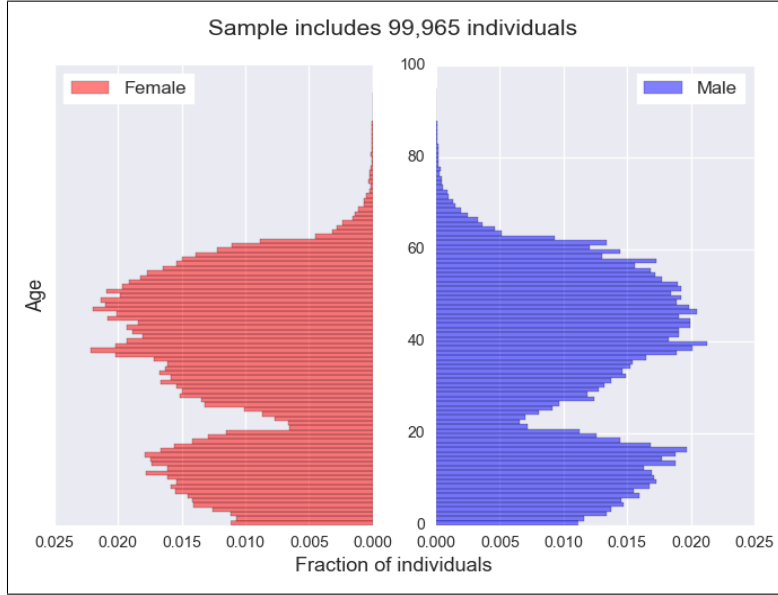


Figure 3: Mean and standard deviation of positive monthly expenditures for individuals by number of positive expenditure months



data. On average, female individuals have higher monthly health expenditures than their male counterparts, but the one with the highest monthly spending is a male. Figure 4 illustrates the age distribution of individuals by gender. For both female and male individuals, the age is distributed in a bimodal fashion with the first peak

Figure 4: The distribution of male and female individuals by age



in late teenage hood and the second peak around the late-40s and early-50s.

3 Model

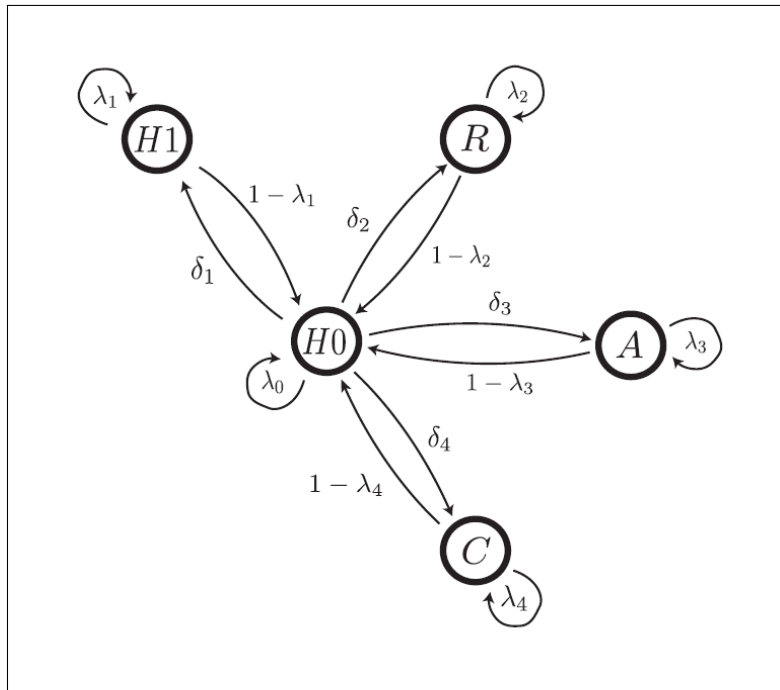
We model health care expenditures as a Markov regime-switching process. [Evans et al. \(2014\)](#) classify health states to five different categories and each individual belongs to one of those five different categories at any given time period t . Those five different categories of health states are: a basic healthy state ($H0$), a really healthy state ($H1$), a regular health-care-consumption state (R), an acute health-care-consumption state (A), and a chronic health-care-consumption state (C). Among those five possible health states, $s \in \{H0, H1, R, C, A\}$, $H0$ and $H1$ would always yield zero monthly health care consumption while the other three states, A , R , and C , would always yield positive monthly health care expenditures.

Two stochastic processes determine an individual's health care expenditure in each period. In the first stochastic process, nature determines the current health state of the individual based on her health state in the previous period. The Markov transition probabilities for this process are depicted in [Figure 5](#). Transition matrix \mathbf{A}

presented in Equation (1) is a right stochastic matrix and represents the probability that an individual who are in the current health state $s \in \{H0, H1, R, C, A\}$ would be in state $s' \in \{H0, H1, R, C, A\}$ in the next period.

As illustrated in Figure 5 as well as the zero elements in the Markov stochastic matrix in Equation (1), an important assumption of our current model is that if an individual leaves one of the positive-expenditure states or the very healthy state $H1$, the individual must spend at least one period in the basic healthy state $H0$ before transitioning to another positive-expenditure state or to the very healthy state. This assumption is essential to identify the probabilities in the Markov transition matrix $\mathbf{A}(\vec{\lambda}, \vec{\delta})$. This assumption is consistent with the notion that all contiguous positive expenditure spells are of the same type of health state. At least two healthy states are required to match zero-expenditure spell lengths in the data.

Figure 5: Markov states diagram for transitions among health states: H0, H1, R, A, and C by Evans et al. (2014)



$$Pr(s'|s) = A(\vec{\lambda}, \vec{\delta}) = \begin{bmatrix} \lambda_0 & \delta_1 & \delta_2 & \delta_3 & \delta_4 \\ 1 - \lambda_1 & \lambda_1 & 0 & 0 & 0 \\ 1 - \lambda_2 & 0 & \lambda_2 & 0 & 0 \\ 1 - \lambda_3 & 0 & 0 & \lambda_3 & 0 \\ 1 - \lambda_4 & 0 & 0 & 0 & \lambda_4 \end{bmatrix} \quad (1)$$

To summarize, if nature assigns an individual to any health state other than $H0$, our model assumption restricts future events of that individual to two possible outcomes: either she would stay in the current non- $H0$ health state or she would go back to $H0$. This makes λ_i the probabilities of an individual staying in the same non- $H0$ health state, and $1 - \lambda_i$ the probabilities of the individual going back to $H0$.

If nature assigns an individual to health state $H0$, five possible outcomes could occur: she could transit to the other four health states, $H1, R, A, C$, from $H0$ or she could possibly stay in $H0$. Since the sum of transition probabilities from $H0$ to other four health states plus the probability of staying in $H0$ must be one, there would be a total of five possible outcomes for her in the next period, among which λ_0 is the probability of staying in $H0$, and δ_s are the probabilities of switching to other health states from $H0$.

Once an individual knows her health state, the second stochastic process draws a health care expenditure level from a distribution specific to that particular health state. The following Section 4 details the estimation of the Markov transition matrix and examines the state-specific health expenditure processes.

4 Estimation

We estimate the parameters $\vec{\lambda} = [\lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4]$ and $\vec{\delta} = [\delta_1, \delta_2, \delta_3, \delta_4]$ of the Markov process described in Section 3. Then, we would use the estimated Markov-process parameters to determine the underlying health state of all positive monthly expenditures. Since the goal of the current section is to test and replicate [Evans et al. \(2014\)](#), we remain agnostic to the specific characteristics of the five health states, including

the three would yield positive health care expenditures. Accordingly, in this section, we use the labels $s \in \{H0, H1, H1, H2, H3\}$ instead of adopting the labels proposed by [Evans et al. \(2014\)](#).

Following [Evans et al. \(2014\)](#), we assume that the number of consecutive zero expenditure months and the number of consecutive positive expenditure months constitute the principal distinguishing characteristic of health states in the data. We estimate $\vec{\lambda}$ and $\vec{\delta}$ by GMM to match moments that represent the number of consecutive zero health expenditure months as well as the number of consecutive positive health expenditure months.

Also, following [Evans et al. \(2014\)](#), we assume that the proportion of people in each of the five health states is constant over time. Let these proportions be given by a state vector $\mathbf{v} = [v_0, v_1, v_2, v_3, v_4]^T$. This ergodic distribution satisfies $\mathbf{v}^T \mathbf{A} = \mathbf{v}^T$. And let $h_{i,t}$ be the monthly health expenditure by individual i in period t . Since the two health states $s = \{H0, H1\}$ would always yield zero health care expenditure at period t , we can directly compute the probability of 0 health care expenditure in the population at any given time period to be $v_0 + v_1 = Pr(h_{i,t} = 0) = 0.5735$. Therefore, the sum of the estimated values of $H0$ and $H1$ should be closed to 0.5735.

4.1 Estimating Markov process

We want to know the probabilities of consecutive nonzero health expenditure periods, so we would define a_k to be the probability that an individual had positive expenditure in the current month given that the individual also had positive expenditure in the previous k months. So, probabilistically, a_k is:

$$a_k = Pr(h_{i,t} > 0 | h_{i,t-1} > 0, \dots, h_{i,t-k} > 0) \quad (2)$$

Let b_k represents the unconditional probability that the current period and the

previous k periods all had positive expenditure.

$$\begin{aligned}
b_k &= Pr(h_{i,t} > 0, h_{i,t-1} > 0, \dots, h_{i,t-k} > 0) \\
&= Pr(h_{i,t} > 0 | h_{i,t-1} > 0, \dots, h_{i,t-k} > 0) \times Pr(h_{i,t-1} > 0, \dots, h_{i,t-k} > 0) \\
&= a_k b_{k-1} = a_k a_{k-1} b_{k-2} = a_k a_{k-1} a_{k-2} b_{k-3} \\
&= \prod_{j=0}^k a_j \quad \text{because } b_0 = a_0
\end{aligned} \tag{3}$$

By taking the cumulative product of $\{a_j\}_{j=0}^k$ we can determine $\{b_j\}_{j=0}^k$. Notice that the consecutive nonzero claims satisfy the following relations based on our model:

$$\begin{aligned}
v_2 + v_3 + v_4 &= b_0 \\
\lambda_2 v_2 + \lambda_3 v_3 + \lambda_4 v_4 &= b_1 \\
\lambda_2^2 v_2 + \lambda_3^2 v_3 + \lambda_4^2 v_4 &= b_1 \\
\lambda_2^3 v_2 + \lambda_3^3 v_3 + \lambda_4^3 v_4 &= b_1 \\
&\vdots \\
\lambda_2^k v_2 + \lambda_3^k v_3 + \lambda_4^k v_4 &= b_1
\end{aligned} \tag{4}$$

Analogously for zero expenditures, let c_k be the probability that an individual had zero expenditure in the current month given that the individual also had zero expenditures in the previous k months. So, c_k is:

$$c_k = Pr(h_{i,t} = 0 | h_{i,t-1} = 0, \dots, h_{i,t-k} = 0) \tag{5}$$

We want to know the probabilities of consecutive zero health expenditure periods. Let d_k represent the unconditional probability that the current period and the

previous k periods all had zero expenditures.

$$\begin{aligned}
d_k &= Pr(h_{i,t} = 0, h_{i,t-1} = 0, \dots, h_{i,t-k} = 0) \\
&= Pr(h_{i,t} = 0 | h_{i,t-1} = 0, \dots, h_{i,t-k} = 0) \times Pr(h_{i,t-1} = 0, \dots, h_{i,t-k} = 0) \\
&= c_k d_{k-1} = c_k c_{k-1} d_{k-2} = c_k c_{k-1} c_{k-2} d_{k-3} \\
&= \prod_{j=0}^k c_j \quad \text{because } d_0 = c_0
\end{aligned} \tag{6}$$

By taking the cumulative product of $\{c_j\}_{j=0}^k$ we can determine $\{d_j\}_{j=0}^k$.

The theoretical probabilities of consecutive positive spells in (4) was simple because each spell is defined as being exclusively in one of the positive health states $s = \{R, A, C\}$. However, zero expenditure spells can bounce between the two healthy states $s = \{H0, H1\}$. The theoretical probabilities of consecutive zero claims satisfy the following recursive relation,

$$\begin{aligned}
d_k &= p_{k-1,0}(\lambda_0 + \delta_1) + p_{k-1,1} \\
p_{k,0} &= p_{k-1,0}\lambda_0 + p_{k-1,1}(1 - \lambda_1) \\
p_{k,1} &= p_{k-1,0}\delta_1 + p_{k-1,1}\lambda_1 \quad \text{for } k = 1, 2, \dots \\
&\text{and } d_0 = v_0 + v_1, \quad p_{0,0} = v_0, \quad p_{0,1} = v_1
\end{aligned} \tag{7}$$

where $p_{k,0}$ is the probability of a zero expenditure spell of length k that ends in state $H0$ and $p_{k,1}$ is the probability of a zero expenditure spell of length k that ends in state $H1$.

Let $\mathbf{b} = [b_0, b_1, \dots, b_23]^T$ and $\mathbf{d} = [d_0, d_1, \dots, d_23]^T$ be the vectors of data moments to match. We estimate the parameters $\vec{\lambda}$ and $\vec{\delta}$ with the resulting ergodic distribution state vector \mathbf{v} by solving the following optimization problem.

$$\begin{aligned}
& \min_{\{\lambda_i\}_{i=0}^4, \{\delta_i\}_{i=1}^3} \|B(\vec{\lambda})\mathbf{v} - \mathbf{b}\|_2 + \|D(\vec{\lambda}, \delta_1, \mathbf{v}) - \mathbf{d}\|_2 \\
& \text{s.t. } \mathbf{v}'A(\vec{\lambda}, \vec{\delta}) = \mathbf{v}' \quad \text{and} \quad \delta_4 = 1 - \lambda_0 - \delta_1 - \delta_2 - \delta_3 \\
& \text{and } \lambda_i, \delta_j \in (0, 1) \quad \forall i, j
\end{aligned} \tag{8}$$

in which,

$$B(\vec{\lambda}) = \begin{bmatrix} 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & \lambda_2 & \lambda_3 & \lambda_4 \\ 0 & 0 & \lambda_2^2 & \lambda_3^2 & \lambda_4^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \lambda_2^{T-1} & \lambda_3^{T-1} & \lambda_4^{T-1} \end{bmatrix} \quad \text{and} \quad D(\vec{\lambda}, \delta_1, \mathbf{v}) = \begin{bmatrix} v_0 + v_1 \\ p_{0,0}(\lambda_0 + \delta_1) + p_{0,1} \\ p_{1,0}(\lambda_0 + \delta_1) + p_{1,1} \\ \vdots \\ p_{22,0}(\lambda_0 + \delta_1) + p_{22,1} \end{bmatrix}.$$

The two norms in (8) match model moments $B(\vec{\lambda})\mathbf{v}$ and $D(\vec{\lambda}, \delta_1, \mathbf{v})$ to data moments \mathbf{b} and \mathbf{d} . Also, note that $d_0 = 1 - b_0$. This GMM estimation, therefore, uses 47 moments to estimate 8 parameters.

Table 2 shows the estimates of the $\vec{\lambda}$ and $\vec{\delta}$ Markov probabilities and the implied ergodic distribution \mathbf{v} . Table 3 and Figure 6 show how closely the estimated model moments \mathbf{b} and \mathbf{d} match their corresponding data moments.

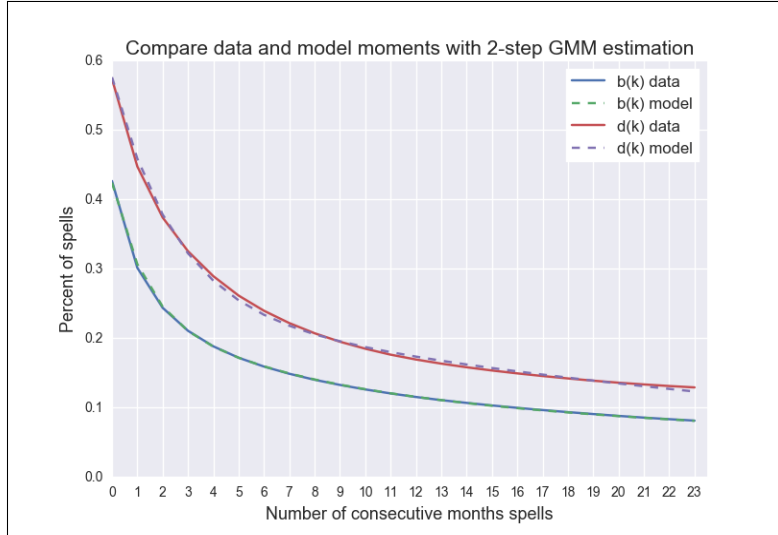
Table 2: Estimated values of $\vec{\lambda}$ and $\vec{\delta}$ and corresponding \mathbf{v}

		λ_s	δ_s	v_s
<i>H0</i>	$s = 0$	0.6698		0.3743
<i>H1</i>	$s = 1$	0.9690	0.0167	0.2017
<i>H2</i>	$s = 2$	0.8465	0.0525	0.1281
<i>H3</i>	$s = 3$	0.9796	0.0069	0.1256
<i>H4</i>	$s = 4$	0.4415	0.2541	0.1703

Table 3: Comparison of model moments to data moments

	model	data		model	data		model	data
b_0	0.4265	0.4240	b_8	0.1400	0.1405	b_{16}	0.0996	0.0991
b_1	0.3014	0.3066	b_9	0.1326	0.1329	b_{17}	0.0964	0.0959
b_2	0.2438	0.2455	b_{10}	0.1261	0.1264	b_{18}	0.0935	0.0930
b_3	0.2106	0.2104	b_{11}	0.1204	0.1206	b_{19}	0.0906	0.0902
b_4	0.1882	0.1879	b_{12}	0.1152	0.1154	b_{20}	0.0880	0.0877
b_5	0.1718	0.1718	b_{13}	0.1107	0.1107	b_{21}	0.0855	0.0853
b_6	0.1591	0.1593	b_{14}	0.1067	0.1065	b_{22}	0.0833	0.0830
b_7	0.1487	0.1491	b_{15}	0.1030	0.1026	b_{23}	0.0812	0.0809
	model	data		model	data		model	data
d_0	0.5735	0.5760	d_8	0.2072	0.2056	d_{16}	0.1493	0.1522
d_1	0.4474	0.4587	d_9	0.1949	0.1955	d_{17}	0.1454	0.1475
d_2	0.3739	0.3781	d_{10}	0.1848	0.1871	d_{18}	0.1420	0.1431
d_3	0.3253	0.3222	d_{11}	0.1762	0.1799	d_{19}	0.1387	0.1388
d_4	0.2893	0.2828	d_{12}	0.1692	0.1734	d_{20}	0.1358	0.1347
d_5	0.2613	0.2545	d_{13}	0.1633	0.1675	d_{21}	0.1333	0.1307
d_6	0.2395	0.2337	d_{14}	0.1581	0.1621	d_{22}	0.1310	0.1269
d_7	0.2217	0.2179	d_{15}	0.1534	0.1570	d_{23}	0.1290	0.1232

Figure 6: Plot of b_k and d_k from model versus data for $k = 0, 1, \dots, 23$



4.2 Identifying health expenditure patterns

Once the parameters for the Markov process $\vec{\lambda}$ and $\vec{\delta}$ and the corresponding ergotically distributed state matrix \mathbf{v} are estimated as in Section 4.1, it is now possible

to determine the underlying health states $s \in \{H0, H1, H2, H3, H4\}$. Healthy states $s \in \{H0, H1\}$ are represented by zero expenditures months. Accordingly, we can categorize all zero expenditures as either $H0$ or $H1$. On the other hand, each positive expenditure spell of length n has a positive probability of being in any of the three healthy states.

Following [Evans et al. \(2014\)](#), we distinguish four positive expenditure spell types for assigning probabilities of being in three healthy states: 1) spells of n consecutive positive expenditures bounded by a beginning month and an ending month with zero expenditures, 2) front-censored spells that start the sample period with n consecutive positive expenditure months, 3) back-censored spells that end the sample period with n consecutive positive expenditure months, and 4) spells with entire sample having positive expenditures.

The probability of each of these four spell types being in any of the positive-expenditure health state are given, in order, by the following four Equations (9) through (12):

$$Pr(h_{i,t} = 0, \{h_{i,j}\}_{j=t-1}^{t-1} > 0, h_{i,t-n-1} = 0) = \sum_{s=2}^4 \delta_s \lambda_s^{n-1} (1 - \lambda_s) \text{ for } 1 \leq n \leq 22. \quad (9)$$

$$Pr(h_{i,n+1} = 0, \{h_{i,j}\}_{j=1}^n > 0) = \sum_{s=2}^4 v_s \lambda_s^{n-1} (1 - \lambda_s) \text{ for } 1 \leq n \leq 23. \quad (10)$$

$$Pr(\{h_{i,j}\}_{j=24-n+1}^{24} > 0, h_{i,24-n} = 0) = \sum_{s=2}^4 \delta_s \lambda_s^{n-1} \text{ for } 1 \leq n \leq 23. \quad (11)$$

$$Pr(\{h_{i,j}\}_{j=1}^n > 0) = \sum_{s=2}^4 v_s \lambda_s^{n-1} \text{ for } n = 24. \quad (12)$$

Figures 7 and 8 illustrate the probability that a spell of n consecutive positive expenditure is in state $s = \{H2, H3, H4\}$ for both uncensored string type (9) and front- and back-censored type (12) of strings. With the computed probabilities with parameters and ergodic distribution shown in Table 2, we can determine the underlying health state of each spell of positive expenditure to be the one with the highest

probability given the length n and the spell type. For our sample of 2,399,916 individual monthly expenditures, all front- and back-truncated strings are of length 24 and, therefore, $s = H3$ health-care-consumption type, which is named as C (chronic) type in [Evans et al. \(2014\)](#). We further stress that our predicted labels for all n for both string types are identical to the predicted labels in [Evans et al. \(2014\)](#).

Figure 7: Percent probability that uncensored positive expenditure string of length n is type s

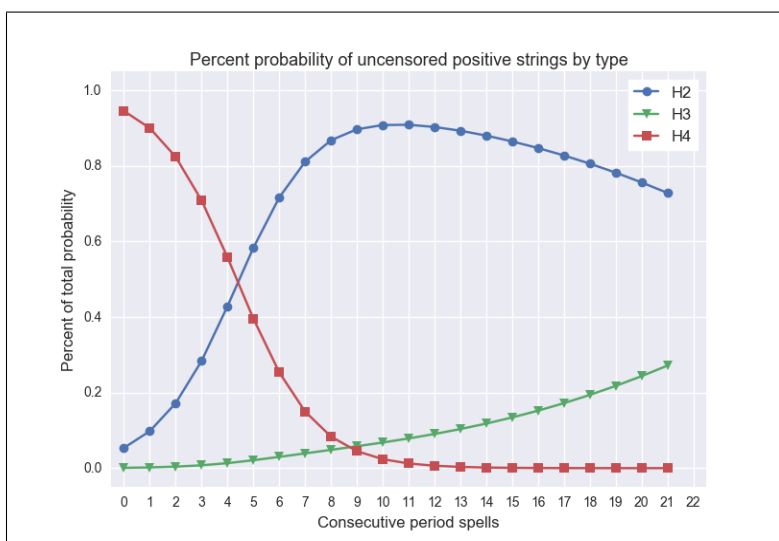
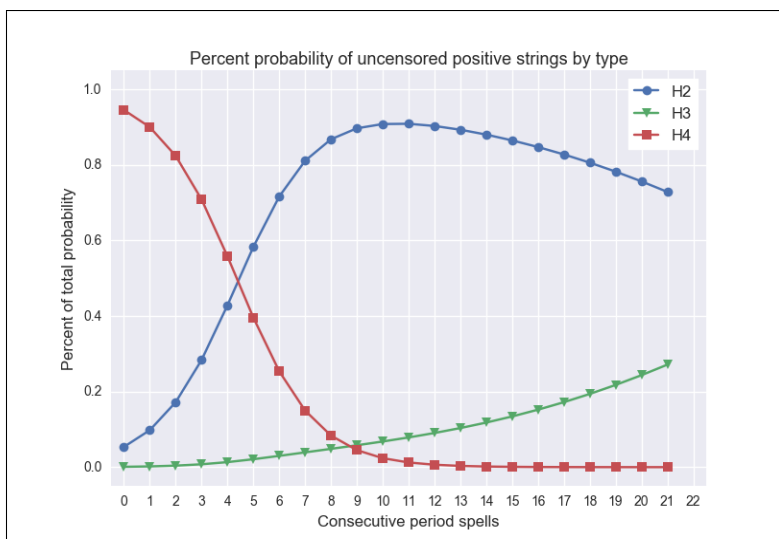


Figure 8: Percent probability that front- and back-censored positive expenditure string of length n is type s



We now explore and examine the characteristics of the three health states determined by the spell length and type of positive expenditures. Table 4 summarizes the characteristics of the positive expenditure of all three health states across gender and age dimensions. Individuals are divided into four age groups: younger than 21 years old, between 21 to 44 years old, between 45 to 64 years old, and older than 65 years old. Although largely arbitrary and with little theoretical justification, our division of age groups serves adequately the purpose of this section, which is exploratory in nature.

Table 4: Comparison of positive expenditure patterns across gender and age

		<i>H2</i>	<i>H3</i>	<i>H4</i>	Total
Count	All	277,056	283,213	462,916	1,023,185
	Female	164,017	169,934	250,234	584,185
	Male	113,039	113,279	212,682	439,000
	Age (< 21)	50,216	27,231	164,519	241,966
	Age (< 45)	101,061	82,189	153,296	336,546
	Age (< 65)	119,435	161,555	139,454	420,444
	Age (\geq 65)	6,344	12,238	5,647	24,229
	Mean	All	798.71	1,073.61	447.46
Female		753.09	1,010.54	431.79	690.35
Male		864.89	1,168.23	465.89	749.86
Age (< 21)		605.37	1,107.95	342.77	483.38
Age (< 45)		742.09	859.14	486.15	654.09
Age (< 65)		917.64	1,157.64	520.78	878.23
Age (\geq 65)		991.94	1,328.38	636.15	1078.95
St. Dev.		All	3,771.12	4,650.51	1,833.88
	Female	3,059.81	3,897.57	1,625.46	2,859.95
	Male	4,611.30	5,591.74	2,052.03	3,947.60
	Age (< 21)	3,606.08	6,251.56	1,538.57	2,950.69
	Age (< 45)	3,212.72	3,741.47	1,893.12	2,735.59
	Age (< 65)	4,232.99	4,731.42	1,999.29	3,875.27
	Age (\geq 65)	3,966.34	4,851.03	3,193.50	4,287.45

Table 4 shows that *H4* is the most common expenditure type in general, except for the over-65-year-old age group for which the most common type is *H3* (50.51%). In fact, the proportion of *H3* type expenditures increase with age (12.67% for the youngest age group, 24.42% for the next age group, and 38.42% for the third age

group). Between male and female, monthly health expenditures by male individuals are more likely to be of $H4$ type (48.45%) than health expenditures by female individuals (42.83%). On the other hand, on average, the most expensive expenditure type is $H3$, the second most expenditure type is $H2$, and the least expensive is $H4$ for the entire sample as well as all subgroups. The same pattern holds for the standard deviation of monthly health expenditure across $s = \{H2, H3, H4\}$. That is, $H3$ is the most expensive expenditure type with the greatest variance. $H2$ is the next most expensive type with the second greatest variance. $H4$ is the least expensive type of health expenditure with the smallest variance.

This, then, leads to our evaluation of the original labels by [Evans et al. \(2014\)](#), namely, $s = \{R, C, A\}$. The comparison of percent probabilities that the positive expenditure string of varying n is of type s between the original study and ours suggests that R (regular), C (chronic), and A (acute) corresponds to our $H4$, $H3$, and $H2$, respectively. We observe that R type expenditures are generally the most common type with the lowest mean and standard deviation. [Figure 7](#) also shows that R type of expenditures have shorter spells other expenditure types. This is also true in cases of front-censored spells and back-censored spells. C type expenditures are more common among older than 65-year-old group and the largest in mean and standard deviation. In addition, C type of expenditure spells consist of at least 13 consecutive months. As [Figure 8](#) shows, all expenditure spells of 24 consecutive months are C type. Finally, A type expenditures appear as a middle stage between the of R and C types in terms of proportion, mean, standard deviation and spell length.

Based on this evaluation, we suggest that the original labels may not be the most appropriate for the corresponding positive health care expenditure patterns. For example, the spell length n for A (acute) type, which can extend up to 23 consecutive month (See [Figure 7](#)) may not fit the medical usages of the term “acute”.² In addition, R for “regular” health-care-consumption state may misrepresent the underlying

²For example, the “acute illness” entry in [Breskin et al. \(2007\)](#) states that the term denotes “a serious illness that appears suddenly but usually does not last long”. This does not seem to best characterize $H2$ health-care-consumption state, which has the positive expenditure spell length of 6 to 23 months.

health condition of an individual characterized by a short-term (i.e., 1 to 5 consecutive months) positive health expenditure. Therefore, we propose an alternative labeling scheme for positive expenditure types $s = \{M, S, C\}$, where M denotes “moderately ill”, S denotes “severely ill”, and C denotes “chronically ill”. M , S , and C in our proposal corresponds to R , A , and C in the original study, respectively.

5 Conclusion

This paper replicates and evaluates a Markov regime-switching approach to estimating individual health care cost dynamics first proposed by [Evans et al. \(2014\)](#). Using the GMM procedure for estimating model parameters as described in the original study, we successfully match the targeted moments to an impressive degree of precision. The model, however, appears sensitive to initial parameter guesses. We also validate the existence of the three distinct types of health care consumption. The estimated probabilities that a truncated or non-truncated string of n consecutive positive expenditure is of a specific health state $s \in \{H2, H3, H4\}$ allow us to label each spell of positive health expenditures. We examine and compare the characteristics of the labelled expenditures with gender and age variables. Our examination suggests that the original labelling scheme of R for regular health-care-consumption state, C for chronic health-care-consumption state, and A for acute health-care-consumption state potentially misrepresents the empirical characteristics of three positive health expenditure states. We then propose an alternative labeling scheme, in which M represents “moderately ill”, S represents “severely ill”, and C represents “chronically ill”.

References

Breskin, Myrna, Kevin Dumith, Enid Pearsons, and Robert Seeman, *McGraw-Hill Medical Dictionary for Allied Health*, McGraw-Hill Higher Education, 2007.

Evans, Richard W., Jeffrey Humpherys, and Sara Taylor, “A Markov Regime-switching Approach to Estimating Health Cost Dynamics,” 2014.

French, Eric and John Baily Jones, “On the Distribution and Dynamics of Health Care Costs,” *Journal of Applied Econometrics*, 2004, 19 (6), 705–721.