Immigration trends' impacts on state vocational rehabilitation agency minority application rates: An empirical forecast model demonstration study

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Abstract.

BACKGROUND: Incessant migration trends of persons of color to the United States warrant the identification of promising forecast models to help state vocational rehabilitation agencies (SVRAs), policy makers, researchers, and advocates inform strategic plans, policy formulation, and research agenda development.

OBJECTIVE: This study demonstrated and assessed the efficacy of two different multivariate empirical forecast models' (i.e., Vector Autoregressive [VAR] model and Multivariable Grey Model [MGM]) ability to accurately predict immigration (Blacks [e.g., Kenya, Nigeria, South Africa, Cameroon], American Indians or Alaskan Natives [e.g., Canada, Mexico], Asians [e.g., China, India, Vietnam, Korea, Japan], Native Hawaiian or other Pacific Islanders [e.g., the Philippines], and Latinos [e.g., Mexico, El Salvador, Guatemala, Cuba, Dominican Republic] trends' impact on new unduplicated application rates among minorities.

METHOD: Nine years of Rehabilitation Services Administration (RSA)-911 case record data (fiscal year [FY] 2006 thru 2014) on SVRA applications and U.S. Census Bureau American Community Survey 1-year estimates (calendar year 2006 thru 2014) on foreign born persons were entered into the VAR model and MGM to test their predictive performance.

RESULTS: The MGM was demonstrated to be superior to the VAR model in predictive accuracy. The MGM three-year forecast projected an upward curve trend trajectory in the percentage of new Black or African American, American Indian or Alaskan Natives, Asians, and Latino SVRA applicants for FYs 2015 thru 2017.

CONCLUSION: The MGM can be considered for use by SVRAs as a promising tool to help them respond appropriately to the needs of new immigrants and other minority group members.

Keywords: Migration trends, minorities, vocational rehabilitation (VR)

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1. Background

Gigantic migration trends among racially and ethnically diverse individuals (Blacks [e.g., Kenya, Nigeria, South Africa, Cameroon], American Indians or Alaskan Natives [e.g., Mexico], Asians [e.g., China, India, Vietnam, Korea, Japan], Native Hawai-

ian or other Pacific Islanders [e.g., the Philippines], and Latinos [e.g., Mexico, El Salvador, Guatemala, Cuba, Dominican Republic]) from economically and/or politically underdeveloped nations to countries that offer economic opportunity and political asylum continue to reshape the world's population. Consequently, nearly every country around the globe has experienced a substantial refashioning of its demographic landscape (Pérez-Armendáriz, 2014; Perez & Hirschman, 2009; Uhlenberg, 2013). The United States (U.S.) is no exception to this phenomenon having experienced an exponentially high incidence of new immigrants from diverse corners of the world during two distinct periods: (a) the initial immigration wave that began in the middle of the nineteenth century and culminated in 1900 with almost nine million legal immigrants, and (b) the second wave that started 1950 and has not come to an end (Chojnicki, Docquier, & Ragot, 2011).

The nation's rapidly changing demography and increasing levels of diversity represent an incitement that has sparked active contemporary legislative debate within the context of current immigration policy (Cross et al., 2015; Ewing, 2010; Ewing, 2012). U.S. immigration policy represents a contemporary hot button issue as policymakers contemplate labor market demands and border security concerns. These alarms center on the estimated 9 million undocumented immigrants who are in many cases the parents and family members of citizen-children with disabilities. As the trend of migration to the U.S. continues to advance, the issue of citizenship and understanding the conditions of naturalization becomes increasingly significant (Cross et al., 2015). While immigrants who become U.S. citizens are granted all of the rights that are conferred to native U.S. citizens, legal permanent residents are granted the legal right to remain in the country permanently and work with a renewable green card as proof of lawful status in the country (Stock, 2012). On the contrary, undocumented immigrants continue to live in the "shadows" having no residency rights and oftentimes relegated to menial agricultural-based and other labor intensive lines of employment (i.e., manufacturing and services) requiring repetitive and rapid body movements and fraught with safety concerns often resulting in a disability (Liu & Painter, 2012; Schulz et al., 2013).

Migration to the U.S. has been attributed to individuals' pursuit of employment opportunities, meaningful wages and an improved quality of life (Bennett, Scornaiencki, Brzozowski, Denis, & Magalhaes, 2012; Kelly, 2010). However, these uncertain migration patterns raise immediate questions regarding the American economy and varied constituencies that are tied to the socio-economic landscape. State vocational rehabilitation agencies (SVRAs), constituent entities, are principle stakeholders that may be heavily impacted by new and emerging racial and ethnic immigration trends. Whether SVRAs have the ability and capacity to deliver services to new minority U.S. citizens, adult legal permanent residents, and citizen-children with disabilities (i.e., school-to-work transition services) is a question that demands immediate attention (Cross et al., 2015).

Potential challenges within SVRA context include cultural and linguistic concerns, health care service access barriers, community participation limitations (i.e., employment, independent living), and the deportation of undocumented family members. For example, Cross et al. (2015) raised the issue that pronounced linguistic and cultural barriers, particularly in communication, may create resistance to services on behalf of the consumers as well as practitioners. More subtle, though not any less prominent, are issues such as little knowledge of rehabilitation services and benefits, cultural mistrust of rehabilitation practitioners and potential employers, low expectations of job placement and little knowledge of and lack of accessibility to technology. The issue of deportation has also been forcefully ventured. For instance, the deportation of mixed-status adult family (i.e., families with citizens and undocumented members) members of citizen-children eligible for SVRA sponsored school-to-work transition services such as parents, grandparents, uncles, aunts, sisters, and brothers erode networks crucial to their success in obtaining and maintaining employment and careers.

By their very nature, unceasing immigration patterns raise concerns about the capacity of the 80 SVRAs across the nation to effectively respond to this growing crisis (Cross et al., 2015). Consequently, there exist a need for promising forecast methods and applications that can be used by SVRAs, policy makers, researchers, and advocates to inform strategic planning, policy formulation, and research program development for improved rehabilitation experiences. To date, however, relatively few studies have forecasted minority SVRA application rate trends, and so these agencies have had little information available to strategically plan for a rapid and effective response to minority immigrants' and U.S. born minorities' needs.

2. Purpose of the study

Although Section 21 of the 1998 Rehabilitation Act Amendments (Public Law 93–112) spawned a plethora of research examining rehabilitation experiences along racial and ethnic lines, scant attention has been paid to understanding SVRA and minority immigrant intersection phenomena. More specific, little information is available on the potential impacts of immigration trends on SVRA application rates. Consequently, there is a need to demonstrate the efficacy of forecast models that can be considered for accurately predicting these trends impacts' on SVRA systems. These trends call for the development of a three-year forecast model to help SVRAs, policy makers, and researchers inform their strategic plans, policy formulation, and future research agendas. The purpose of this study was to demonstrate and assess the efficacy of select multivariate empirical forecast models' (i.e., Vector Autoregressive [VAR] model and Multivariable Grey Model [MGM]) ability to accurately predict immigration trends' impact on SVRA new application rates among minorities. The following research questions were addressed:

1) Which forecast model (i.e., VAR model versus MGM) demonstrates the highest level of accuracy in predicting new SVRA application rate trends?
2) What is the three-year (FYs 2015 to 2017) forecast of the impacts of racial and ethnic immigration trends on SVRA minority application rates?

3. Methods

3.1. Sources of data

Nine years of national Rehabilitation Services Administration (RSA)-911 case record data (FY 2006 to FY 2014 [October 1, 2005 thru September 30, 2014]) on SVRA applicants and U.S. Census Bureau American Community Survey (ACS) 1-year estimates (Calendar Year 2006–2014 [January thru December]) on the foreign born populations were entered into the VAR model and MGM to develop a three-year forecast of new SVRA application rate trends. The subsequent section provides a brief description of each data source.

3.1.1. RSA-911 data

The RSA-911 database contains two distinct variables for race and ethnicity as defined in the most recent Reporting Manual for the Case Service Report. Mutually exclusive race categories were created in this study to include: "Black or African American", "American Indian or Alaska Native", "Asian", "Native Hawaiian or Other Pacific Islander", "White", and "Other" where individuals identified themselves as multiracial or their case contained a missing value. The ethnicity-Hispanic or Latino variable was coded either yes (i.e., Latino/Hispanic) or no (i.e., not Hispanic/Latino). Individuals who identified as Latino may belong to any racial group. The "Date of Application" variable, which includes the year, month, and date that the SVRA received a completed and signed application form from the applicant, was used exclusively to eradicate data duplication and select case records included in the analysis. That is, only unduplicated case records representing individuals who applied for services in the same or "current" FY of the database were included for analysis. For example, if a case record for FY 2011 data indicated that the individual applied for services in FY 2009, that record was excluded from analysis. A detailed account of case record data on application frequencies and percentages broken out by race and ethnicity across the time series are presented in Table 1. The PROC DATA and PROC FREQ procedures in SAS version 9.4 were used to calculate these statistics. (SAS Institute, 2014).

3.1.2. U.S. census bureau data

The ACS data source is a cross sectional survey that draws a new sample of individuals each calendar year and implements a large scale general survey designed to make estimates on various characteristic levels, e.g. race and ethnicity (Reamer, 2010). We obtained ACS 1-year estimates on the foreign born population's select characteristics (i.e., race and ethnicity) for calendar years 2006 thru 2014 data through the following website ink: http://factfinder.census.gov/faces/nav/jsf/pages/community_facts.xhtml. These data include frequencies and percentages on race and ethnicity, as well as other demographics such as age and educational attainment. For race, the ACS estimates provide 5 response categories plus the "some other race" and "two or more races" groupings. We collapsed the "some other race" and "two or more race" categories in the ACS data source to build the "other" level. Data from the race variable levels for "Black

Table 1

The frequency and percent of new unduplicated SVRA applicants and foreign born individuals in the U.S. by race/ethnicity and fiscal year

Year	Time series	RSA		Foreign Born Population	
		$x_1^{(0)}(k)$	%	$x_2^{(0)}(k)$	%
African American or Black					
2006	1	41560	25.65	2928728	7.8
2007	2	41426	25.60	2968656	7.8
2008	3	43148	25.38	3074836	8.1
2009	4	41695	25.65	2811758	7.3
2010	5	43726	26.21	3316336	8.3
2011	6	42181	26.89	3391740	8.4
2012	7	40553	26.88	3470096	8.5
2013	8	37669	25.80	3555934	8.6
2014	9	33400	24.88	3679386	8.7
American Indian or Alaska Native					
2006	1	2285	1.41	150191	0.4
2007	2	2249	1.39	494776	1.3
2008	3	2261	1.33	151844	0.4
2009	4	2276	1.40	231103	0.6
2010	5	2369	1.42	159823	0.4
2011	6	2322	1.48	121134	0.3
2012	7	2172	1.44	163299	0.4
2013	8	2088	1.43	124044	0.3
2014	9	2148	1.6	169167	0.4
Asian					
2006	1	1507	0.93	8786183	23.4
2007	2	1473	0.91	8905968	23.4
2008	3	1513	0.89	8996742	23.7
2009	4	1447	0.89	6971619	18.1
2010	5	1451	0.87	9789184	24.5
2011	6	1443	0.92	10013709	24.8
2012	7	1478	0.98	10328638	25.3
2013	8	1431	0.98	10585105	25.6
2014	9	1413	1.05	11080450	26.2
Native Hawaiian or Other Pacific Islander					
2006	1	567	0.35	75096	0.2
2007	2	534	0.33	114179	0.3
2008	3	578	0.34	113883	0.3
2009	4	520	0.32	115552	0.3
2010	5	517	0.31	79912	0.2
2011	6	502	0.32	121134	0.3
2012	7	468	0.31	122474	0.3
2013	8	438	0.30	124044	0.3
2014	9	393	0.29	126875	0.3
White					
2006	1	113485	70.04	17009148	45.3
2007	2	113583	70.19	17393280	45.7
2008	3	119686	70.40	18562897	48.9
2009	4	113510	69.83	19489720	50.6
2010	5	115245	69.08	19138854	47.9
2011	6	107610	68.60	19502506	48.3
2012	7	101804	67.48	19677485	48.2
2013	8	98654	67.57	19847072	48.0
2014	9	89047	66.33	20088602	47.5
Other					
2006	1	2609	1.61	8560896	22.8
2007	2	2557	1.58	8525371	22.4
2008	3	2822	1.66	7022773	18.5
2009	4	3088	1.90	8974516	23.3
2010	5	3503	2.10	7431789	18.6
2011	6	2808	1.79	7268015	18.0
2012	7	4375	2.90	7144315	17.5

(*Continued*)

Table 1
(*Continued*)

Year	Time series	RSA		Foreign Born Population	
		$x_1^{(0)}(k)$	%	$x_2^{(0)}(k)$	%
Total					
2013	8	5723	3.92	7111867	17.2
2014	9	7855	5.85	7189605	17.0
2006	1	162029	100	37547789	100
2007	2	161822	100	38059694	100
2008	3	170008	100	37960935	100
2009	4	162552	100	38517234	100
2010	5	166829	100	39955854	100
2011	6	156866	100	40377860	100
2012	7	150866	100	40824658	100
2013	8	146003	100	41348066	100
2014	9	134256	100	42291794	100
Hispanic or Latino					
2006	1	16041	9.90	17722556	47.2
2007	2	16732	10.34	18078355	47.5
2008	3	18395	10.82	17803679	46.9
2009	4	17100	10.52	22725168	59.0
2010	5	18518	11.10	18819207	47.1
2011	6	17585	11.21	18816083	46.6
2012	7	16414	10.88	18860992	46.2
2013	8	16820	11.52	18978762	45.9
2014	9	15404	11.47	19327350	45.7

or African American", "American Indian or Alaska Native", "Asian", "Native Hawaiian or other Pacific Islander", "White" and "Other" categories were used in these analyses. The Hispanic or Latino origin variable has two categories; a "Hispanic or Latino" (of any race) level and a "White alone, not Hispanic or Latino" level. We used the "Hispanic or Latino" variable in a separate analysis. A detailed account of frequencies and percentages on foreign-born individuals broken out by race and ethnicity across the time series can be seen in Table 1.

3.2. Forecasting models and data analysis

The selection of an appropriate model(s) is paramount for demonstrating methods that accurately predict and forecast the output. Although researchers have developed quantitative forecasting methods recently, no existing model is perfect in its prediction accuracy in all circumstances or conditions. The VAR model in economics was introduced as an alternative to traditional large-scale macroeconometric models (Sims, 1980). One advantage of the model is that it provides a systematic way to capture rich dynamics in multivariate time series, and the approach has become increasingly popular in recent decades (Lütkepohl, 2009, 2011). The VAR model is an approximation to larger structural systems and

has shown optimal performance with extended time series historical data (Dekimpe & Hanssens, 2000). One limitation of the VAR model is that it has to be estimated to low order systems. That is, the effects of omitted variables are placed in the residuals, which may lead to major distortions in the impulse responses (Armstrong, 2001).

The Grey system theory was developed originally in 1985 (Julong, 1985). The model's focal point is uncertain systems forecasting where small amounts of data, discrete data and incomplete information (e.g. intervals, probability distributions, fuzzy sets, and imprecise probability distributions) are difficult for probability and fuzzy mathematics to handle (Li et al., 2007; Shen et al., 2013). The Grey Model (GM) is based on the grey system theory and has been widely applied in economics and financial areas (Kayacan, Ulutas, & Kaynak, 2010; Li et al., 2007; L. Liu, Wang, Liu, & Li, 2014), public health and biostatistics (Feng & Zhang, 2012; Jin et al., 2008; Shen et al., 2013), engineering (Kang & Zhao, 2012) as well as other specialties.

The Multivariable Grey Model (MGM) (1, n) represents an expansion and complements the grey system model. The MGM has been shown to possess a higher level of predictive performance than the GM (Jun, Jianming, & Yingjun, 1997). The model is designed to work with systems where available
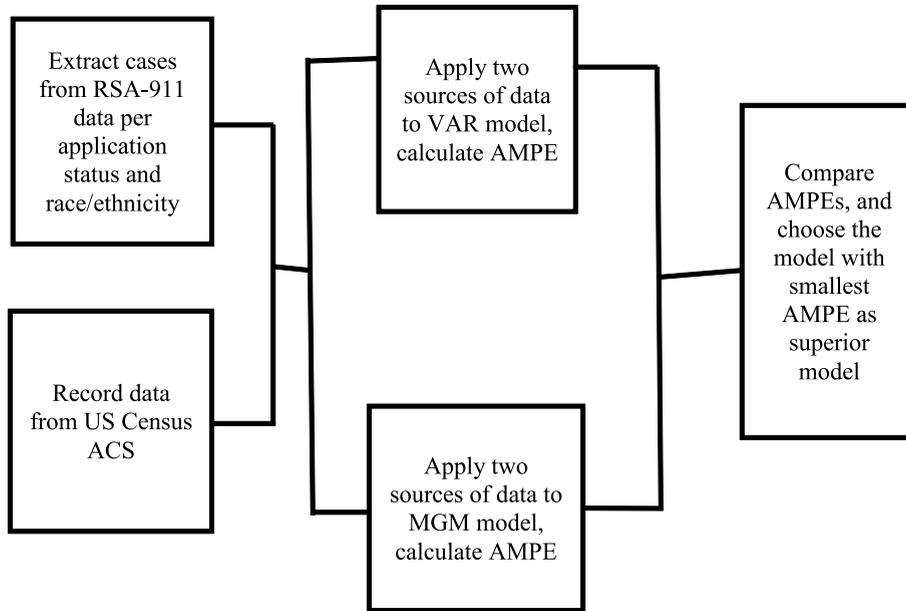
Fig. 1. Research paradigm for forecast modeling.

information is insufficient to characterize the system, and where a complex relationship between response variables and the main influencing factors exists. The benefits of the MGM is that it has higher demonstrative accuracy prediction than traditional multivariate forecasting models (Jun et al., 1997; Pao, Fu, & Tseng, 2012).

In this article, nine years of data from two different sources (i.e., RSA-911 and ACS) were entered into these two different empirical forecast models (i.e., VAR and MGM [1, 2]) to test their predictive accuracy using Absolute Mean Percentage Error (AMPE) as the criterion. A final predictive model was selected based on smallest AMPE to develop the three-year forecast of SVRA application rate trends. Figure 1 shows the research paradigm for the forecast model demonstration and assessment.

The algorithms utilized to reduce the data in the VAR model and MGM (1, 2) follow.

Model 1: Vector Autoregressive (VAR) model

The VAR model was used to analyze the dynamic effects of the ACS data on the foreign born population and SVRA application rates in the RSA-911 databases. The basic modeling procedures are presented below.

Step 1. Obtaining original series. Let $X_t = (x_{1t}, x_{2t}, ..., x_{nt})'$ denote a (n × 1) vector

of time series variables. In this case, $n = 2$ and $t = 8$.

Step 2: VAR Model. The basic p-lag vector autoregressive (VAR (p)) model has the form

$$X_t = c + \Pi_1 X_{t\text{-}1} + \Pi_2 X_{t\text{-}2} + \cdots \Pi_p X_{t\text{-}p}$$
$$+\varepsilon_t, \text{t} = 1, \cdots \text{T} \qquad (1)$$

where Π_i are (n × n) coefficient matrices and ε_t is an (n × 1) unobservable zero mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix $\sum$. For example, the simple VAR (1) model equation has the following form

$$\begin{pmatrix} x_{1t} \\ x_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{pmatrix} \begin{pmatrix} x_{1t-1} \\ x_{2t-1} \end{pmatrix}$$
$$+ \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

or

$$x_{1t} = c_1 + \pi_{11}x_{1t-1} + \pi_{12}x_{2t-1} + \varepsilon_{1t}$$
$$x_{2t} = c_2 + \pi_{21}x_{1t-1} + \pi_{22}x_{2t-1} + \varepsilon_{2t}$$

Step 3: Estimation in R. The function VAR in the package *vars* was used to predict and forecast the time series sequences.

Model 2: Multivariable Grey Model

MGM procedures were employed to develop a three-year forecast of SVRA application rate trends across racial and ethnic populations using nine years (FY 2006–2014) of RSA-911 data and ACS data denoted as $X_1^{(0)}$ and $X^{(0)}$ in Table 1, respectively. The basic procedures of modeling are presented below.

Step1: **Obtaining original series.** A non-negative sequence of raw data $X^{(0)}$ with n samples was expressed as:

$$X_i^{(0)} = (X_i^{(0)}(1), X_i^{(0)}(2), \ldots X_i^{(0)}(n)) \ n \geq 4,$$

where i$=1, 2, \cdots J$ and J was the variable.

Step 2: **Pre-processing of the original raw data.**
a) Accumulating Generation Operator (AGO). A new sequence $X_i^{(1)}$ was: generated by

$$\text{AGO as: } X_i^{(1)} = (x_i^{(1)}(1), x_i^{(1)}(2), \cdots x_i^{(1)}(n)),$$
$$n \geq 4 \qquad (2)$$

where, $x_i^{(1)}(1) = x_i^{(0)}(1)$, and $x_i^{(1)}(k) = \sum_{j=1}^{k} x_i^{(0)}(j), k = 1, 2, \ldots, n, \ j = 1, 2, \ldots J,$
b) The Mean operation. The generated mean sequence of $Z^{(1)}$ was defined as:

$$Z_i^{(1)} = (z_i^{(1)}(1), z_i^{(1)}(2), \ldots z_i^{(1)}(n)) \quad (3)$$

where, $z_i^{(1)}(k)$ was the mean value of adjacent data, i.e.,

$$z_i^{(1)}(k) = 0.5x_i^{(1)}(k) + 0.5x_i^{(1)}(k-1),$$
$$k = 2, 3, \ldots, n \qquad (4)$$

Step 3: **MGM (1, J) Model equation.** The MGM (1, J) model was constructed by establishing a J variable first order differential equation for $x_i^{(1)}(k)$ expressed as:

$$\begin{cases} \frac{dx_1^{(1)}}{dt} = a_{11}x_1^{(1)} + a_{12}x_2^{(1)} + \cdots + a_{1J}x_J^{(1)} + b_1 \\ \frac{dx_2^{(1)}}{dt} = a_{21}x_1^{(1)} + a_{22}x_2^{(1)} + \cdots + a_{2J}x_J^{(1)} + b_2 \\ \vdots \\ \frac{dx_J^{(1)}}{dt} = a_{J1}x_1^{(1)} + a_{J2}x_2^{(1)} + \cdots + a_{JJ}x_J^{(1)} + b_J \end{cases}$$
$$(5)$$

Step 4: We took the inverse AGO (IAGO) to find the predicted values of the primitive sequence by using the IAGO:

$$\frac{\partial X^{(1)}(k)}{\partial t} + AX^{(1)} = B$$

The parameter A and B was estimated by the least square method:

$$\hat{a}_i = \begin{bmatrix} \hat{a}_{i1} \\ \hat{a}_{i2} \\ \vdots \\ \hat{a}_{iJ} \\ \hat{b}_i \end{bmatrix} = (L^T L)^{-1} L^T Y_i \ (i = 1, 2 \cdots J),$$

where

$$L = \begin{bmatrix} z_1^{(1)}(1) & z_2^{(1)}(1) & \cdots & z_J^{(1)}(1) & 1 \\ z_1^{(1)}(2) & z_2^{(1)}(2) & \cdots & z_J^{(1)}(2) & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ z_1^{(1)}(n) & z_2^{(1)}(n) & \cdots & z_J^{(1)}(n) & 1 \end{bmatrix}$$

and

$$Y_i = (x_i^{(0)}(2), x_i^{(0)}(3), \ldots x_i^{(0)}(n)).$$

$$\hat{A} = \begin{bmatrix} \hat{a}_{11} & \hat{a}_{12} & \cdots & \hat{a}_{1J} \\ \hat{a}_{21} & \hat{a}_{22} & \cdots & \hat{a}_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{a}_{J1} & \hat{a}_{J2} & \cdots & \hat{a}_{JJ} \end{bmatrix} \text{ and } \hat{B} = \begin{bmatrix} \hat{b}_1 \\ \hat{b}_2 \\ \vdots \\ \hat{b}_n \end{bmatrix}$$

The solution, also known as time response function, of the above equation was given by:

$$X^{(1)}(k + 1) = e^{-Ak} X^{(1)}(1) + A^{-1}(e^{Ak} - I) \bullet B. \quad (6)$$

Therefore, the fitted and predicted vector sequence $\hat{X}^{(0)}$ was given as:

$$\hat{X}^{(0)}(1) = X^0(1)$$
$$X^{(0)}(k + 1) = \hat{X}^{(1)}(k + 1) - \hat{X}^{(1)}(k) \ k = 1, 2, 3 \cdots$$

3.2.1. Error analysis and validation

In order to evaluate the prediction accuracy of the VAR model and MGM (1, 2), the Absolute Mean Percentage Error (AMPE) criterion was used to estimate model performances and reliability. AMPE is a general accepted percentage measure of prediction accuracy. This indicator was calculated as:

Table 2
The models' predictive accuracy performance- Absolute Mean Percentage Error (AMPE)

RACE / Ethnicity	VAR	MGM(1, 2)
African American/Black	1.87	2.88
AI/AN	2.71	2.69
Asian	1.51	1.24
NH/OPI	6.08	4.58
White	3.60	2.09
Total	2.75	1.94
Latino	4.27	3.84
Mean	3.25	2.75

Note: AI/AN = American Indian or Alaska Native, NH/OPI = Native Hawaiian or Other Pacific Islander.

$$AMPE = \frac{1}{N} \sum_{k=1}^{N} |\frac{e(k)}{x^{(0)}(k)}| \times 100\%,$$

where, $e(k) = x^{(0)}(k) - \hat{x}^{(0)}(k)$.

Table 2 shows the AMPE of the two forecasting models across race and ethnicity. The model with the smallest mean AMPE was selected as the best forecasting model.

3.3. Simulation results

As can be drawn from the results presented in Table 2, the MGM's level of predictive accuracy was much higher than the VAR model's level (i.e., smaller results translate to higher predictive accuracy). The mean AMPE was enhanced from 3.25% for the VAR to 2.75% for the MGM.

The results point out that the MGM was superior in regard to predictive accuracy levels when compared to the VAR model. The MGM (1, 2) results demonstrate that the model can reflect the relationship of restriction and stimulation between the number of new unduplicated applicants and the foreign born population across racial and ethnicity variables. As shown in the Table 3, the MGM projected three-year (i.e., FYs 2015, 2016, and 2017) total frequencies for new applicants included 133,043, 123,920 and 108,713 individuals, respectively. Compared to the FY 2014 baseline total unduplicated application frequency (N = 135,319), FYs 2015 to 2017 projections represent a 1.68%, 8.42%, and 19.02% decrease in new applicants overall. In comparison to this same baseline, the number of new Black or African American applicants were projected to decrease by 2.52%, 2.61% and 5.51% during FY 2015, FY 2016 and FY 2017 respectively; new Native Hawaiian or Other Pacific Islander applicants were projected to decrease

by 5.64%, 16.70% and 30.35%; and new White applicants were projected to decrease by 1.69%, 6.78%, and 13.70% for that same time series. The model projected an increase in the number of new American Indian or Alaska Native applicants by 1.44% in FY 2015 and a decrease of 1.20% and 3.80% in FY 2015 and FY 2016, respectively, when compared to FY 2014 baseline results. Remarkably, the numbers of new Asian applicants were projected to increase by 4.42%, 7.09%, and 12.20% across the same time series when compared to FY 2014 baseline results. Within this comparative context, the model also strikingly projected that the number of new Latino applicants would decrease by 1.82%, 5.7% and 10.47% during FY 2015 to FY 2017, respectively.

Figure 2 shows the frequency curves of new SVRA service applicants for the two models from FY 2006 to FY 2014 and the three-year forecast projections (FY 2015 to FY 2017) for each racial and ethnic target group. Several conclusions can be drawn from these results. First, they indicate that the MGM's (1, 2) predictive value was more closely aligned to the actual number of new applicants than the VAR model generated number confirming that the former model was more accurate than the VAR model. Second, the MGM's (1, 2) curve showed a striking three-year projected upward trend trajectory for the number of new Asian applicants, while such curve trends for Black or African American, Native Hawaiian or Other Pacific Islander, White, and Latino applicants decreased. Third, the curve projects that the number of new Native American applicants will slightly increase in FY 2015 and then decrease during the two subsequent fiscal years. Last, the total number of new applicants for SVRA services were projected to decrease over the three-year forecast time series.

Figure 3 shows the percentage curves of new applicants for each model across nine years (i.e., FY 2006 to FY 2014) for each racial and ethnic target cohort. These results project an increase in the percent of new Black or African American, American Indian or Alaska Native, Asian, and Latino applicants for FYs 2015 to 2017. On the contrary, however, projections indicate that the percentage of applications from Whites and Native Hawaiian or Other Pacific Islander will decrease.

4. Discussion

This study sought to address the following two research questions: (1) Which forecast model

Table 3
The predictive (2006–2014) and forecast model (2015–2017) for the number of new applications by race and ethnicity and time series

Year	Time series	RSA	VAR	MGM
African American or Black				
2006	1	41560	41560	41560
2007	2	41426	42333	42016
2008	3	43148	41914	42681
2009	4	41695	43054	43094
2010	5	43726	43279	43134
2011	6	42181	42028	42625
2012	7	40553	39837	41318
2013	8	37669	37535	38858
2014	9	33400	33820	35682
2015 (F)	10		28290 (−16.35%)	34782 (−2.52%)
2016 (F)	11		20420 (−39.62%)	34752 (−2.61%)
2017 (F)	12		8557 (−74.70%)	33716 (−5.51%)
American Indian or Alaska Native				
2006	1	2285	2285	2285
2007	2	2249	2247	2222
2008	3	2261	2290	2303
2009	4	2276	2232	2286
2010	5	2369	2257	2248
2011	6	2322	2304	2205
2012	7	2172	2266	2162
2013	8	2088	2176	2120
2014	9	2148	2113	2079
2015 (F)	10		2161 (2.27%)	2109 (1.44%)
2016 (F)	11		2174 (2.89%)	2054 (−1.20%)
2017 (F)	12		2182 (3.27%)	2000 (−3.80%)
Asian				
2006	1	1507	1507	1507
2007	2	1473	1468	1487
2008	3	1513	1460	1479
2009	4	1447	1467	1470
2010	5	1451	1472	1461
2011	6	1443	1448	1452
2012	7	1478	1444	1443
2013	8	1431	1449	1434
2014	9	1413	1437	1424
2015 (F)	10		1428 (−0.63%)	1487 (4.42%)
2016 (F)	11		1423 (−0.97%)	1525 (7.09%)
2017 (F)	12		1425 (−0.83%)	1598 (12.20%)
Native Hawaiian or Other Pacific Islander				
2006	1	567	567	567
2007	2	534	548	563
2008	3	578	513	551
2009	4	520	561	538
2010	5	517	499	523
2011	6	502	494	506
2012	7	468	479	485
2013	8	438	442	459
2014	9	393	442	425
2015 (F)	10		358 (−19.00%)	401 (−5.65%)
2016 (F)	11		324 (−26.70%)	354 (−16.70%)
2017 (F)	12		287 (−35.06%)	296 (−30.35%)
White				
2006	1	113485	113485	113485
2007	2	113583	116023	115941
2008	3	119686	114928	116001
2009	4	113510	117304	115055
2010	5	115245	108353	112941
2011	6	107610	111149	109481
2012	7	101804	102508	104476

(Continued)

Table 3
(*Continued*)

Year	Time series	RSA	VAR	MGM
2013	8	98654	96253	97709
2014	9	89654	92628	88940
2015 (F)	10		82283 (−11.17%)	87430 (−1.69%)
2016 (F)	11		75626 (−18.35%)	81502 (−6.78%)
2017 (F)	12		69130 (−25.36%)	70494 (−13.5%)
Total				
2006	1	162029	162029	162029
2007	2	161822	166548	165956
2008	3	170008	163795	165816
2009	4	162552	168401	164861
2010	5	166829	161792	162828
2011	6	156866	156485	159376
2012	7	150866	149317	154059
2013	8	146003	144003	146294
2014	9	134256	138862	135319
2015 (F)	10		127583 (−8.12%)	133043 (−1.68%)
2016 (F)	11		119400 (−5.71%)	123920 (−8.42%)
2017 (F)	12		110000 (−10.47%)	108713 (−19.02%)
Latino / Hispanic				
2006	1	16041	16041	16041
2007	2	16732	16598	17569
2008	3	18395	16807	17592
2009	4	17100	17012	17574
2010	5	18518	18087	17494
2011	6	17585	17299	17325
2012	7	16414	17143	17024
2013	8	16820	16959	16530
2014	9	15404	17058	15754
2015 (F)	10		16924 (−0.79%)	15468 (−1.82%)
2016 (F)	11		16639 (−2.45%)	14855 (−5.71%)
2017 (F)	12		17073 (0.09%)	14104 (−10.47%)

(i.e., VAR model versus MGM) demonstrates the highest level of accuracy in predicting new SVRA application rates?, and (2) What is the three-year (FY 2015 to 2017) forecast of the impacts of racial and ethnic immigration trends on SVRA minority application rates? In regard to research question #1, the findings indicated that the MGM was superior to the VAR model in regard to predictive performance. Consequently, the MGM has promise for use among SVRA leaders, policy makers, and researchers as an accurate forecasting tool to generate predictions that could inform their strategic plan development, policy formulation, and future research program development. Forecasting models are commonly used in business and economics, meteorology and environmental sciences, such as hydrology. For example in business, conceiving a means to predict stock market returns has been a well anticipated goal of some financial practitioners as such forecasting have hefty impacts on the overall stock firms performance and profits. To this end, Van Gysen, Huang, and Kruger (2013) conducted a comprehensive comparison of the predictive accuracy of linear and non-linear models when forecasting financial returns, using a number of macroeconomic variables on the Johannesburg Stock Exchange. In meteorological context, Fu, Lee, Wang, Wang, and Vitart (2013) assessed the prediction skill of the boreal summer intraseasonal oscillation (BSISO) in four state-of-the-art forecasting models for the annual Asian summer monsoon, an occurrence which holds both meteorological and hydrological implications. Although such forecasting models have been confirmed as useful in the aforementioned areas, the literature is void of any such approaches for predicting SVRA application rate trends among minorities. Additional multiple demonstration trials that build upon these results, nonetheless, are needed to either confirm or refute the MGMs' veracity in curve fitting performance.

In addressing research question #2, the results indicate two remarkable projections. First, the number Asian applicants, when compared to the FY 2014 baseline frequency, are projected to increase by 4.42%, 7.09%, and 12.20% for FYs 2015 to FY 2017, respectively. This projection represents a whopping 23% compound percent change (+) in applications
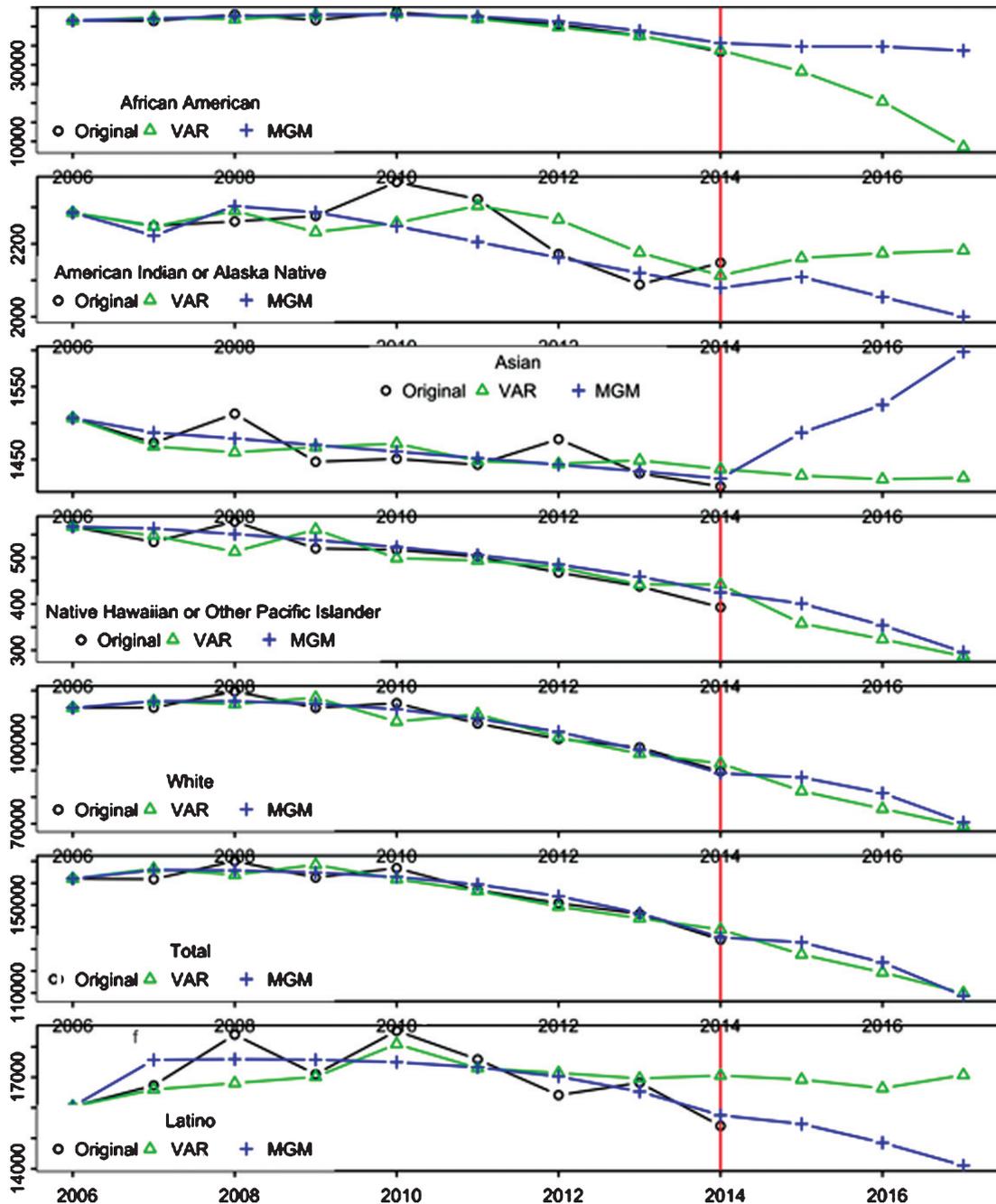
Fig. 2. Forecast for number of new applicants by different models for FYs 2015–2017.

(i.e., from FY 2014 to FY 2017). This finding can be perhaps explained by the substantial number of foreign born Asians residing in the U.S. As reflected in Table 1, over the past ten years, with the exception of calendar year 2009, Asians have represented almost one-quarter of all foreign persons in the U.S. These immigration trends are undeniable, and their impacts on such projections call for SVRAs to pay particular attention to this target population. The finding may have several service and policy implications for SVRAs serving foreign born and U.S. born Asians (e.g., China, India, Vietnam, Korea, Japan) who embrace exotic cultural traditions of their parents, grandparents, and extended family members.
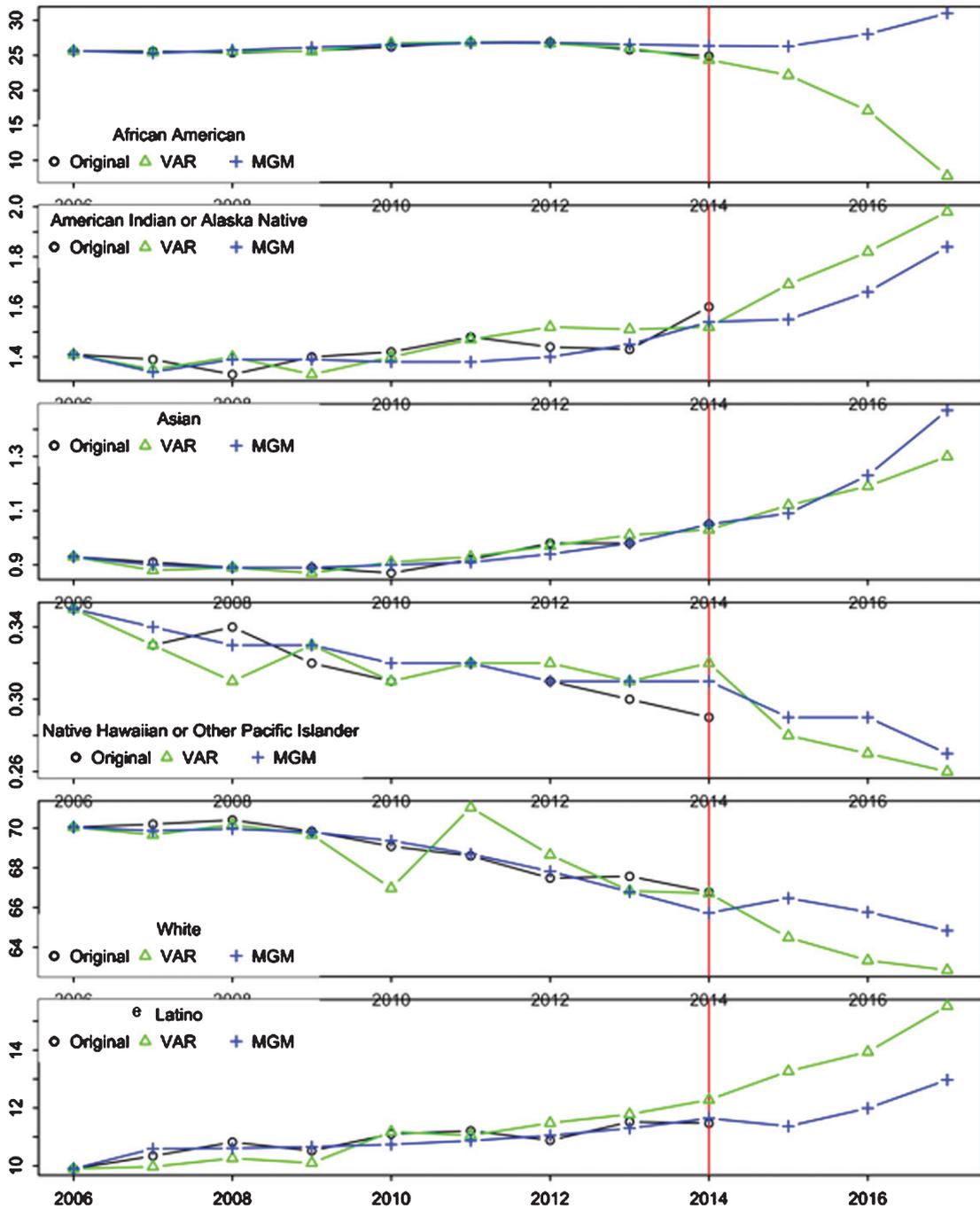
Fig. 3. Forecast for percent of new applicants by different models for FYs 2015–2017.

Second, the findings suggest an upward curve trend trajectory in the percentage of new Black or African American, American Indian or Alaskan Natives, Asians, and Latino applicants for FYs 2015 thru 2017. While the curves suggest that the three-year projected percentages of Blacks or African Americans, American Indians or Alaska Natives, Asians, and Latinos applying for services are anticipated to wax, the percentages for White and Native Hawaiian or Other Pacific Islander applicants are projected to wane. Although the overall number of Black or African American and Latino applicants

were projected to decrease for FYs 2015 to 2017 and American Indian or Alaska Native applicants were projected to decrease for FYs 2016 and 2017 when compared to FY 2014 baseline frequencies, the curves indicate these target groups' percentage of the overall applicant pool will show an increase over the three-year projection period. This finding can be attributed to the fact that the total number of projected applicants will decline more rapidly than the number of new African Americans or Blacks, Latino, or American Indian or Alaska Native applicants.

The bridge between culture and disability is intricate. As such, providing culturally sensitive care to minority immigrants with disabilities can be arduous because of language barriers and differences in values and beliefs (Bal & Perzigian, 2013; Lindsay, Tétrault, Desmaris, King, & Piérart, 2014). Most research on culturally sensitive care and services emphasize ethnic-minority groups as a whole, very little is known about immigrants. Differences between immigrant families and practitioners can significantly impact successful outcomes. Therefore, practitioners should be aware that immigrant families may have conflicting views about disability, establishing the need and having access to various health and rehabilitation related services (Lindsay et al., 2014). Because most practitioners are trained from a western perspective and lack training in working with families from diverse backgrounds, SVRAs should be prepared to develop strategies that allow their personnel to work effectively in circumstances that may require additional cross-cultural competencies.

A second point for practitioners to consider while working with individuals from these diverse immigrant groups (i.e., Blacks, American Indian or Alaska Natives, Asians, and Latinos) is being able to understand the complexities of immigrants' family dynamics. In the U.S. immigrant families are increasingly composed of members of varying legal status or mixed-status families (Zayas & Bradlee, 2014). Approximately 4.5 million of the 5.5 million children of undocumented parents are U.S. citizens. Because of the nature of this demography, it is no longer possible to enforce immigration laws without directly affecting millions of U.S. citizens (Zayas & Bradlee, 2014). Deportation is an issue of critical concern. In light of removal strategies, increasing arrests and detention of undocumented immigrants, tremendous hardship is placed on citizen-children of undocumented immigrants. For example, a Latino high-school student with a disability receiving SVRA sponsored school-to-work transition services whose undocumented mother is deported is likely to experience many adjustment challenges that could result in the failure to place and maintain employment. In essence, the government may be creating two classes of vulnerable citizen-children with disabilities: exiles (those children who go with their parents to another country, often one they do not know) and orphans (those children whose parents leave them in the U.S. in the care of others, sometimes in the child welfare system). Government policies and procedures relating to immigration laws may force undocumented immigrant parents to face awfully distressing choices (Zayas & Bradlee, 2014).

While the above scenario may seem far-reaching as a possible consideration for SVRA professionals in practice, the root of such a buildup has been pronounced as a regular national headline as of late; that being, deportation. More than 400,000 undocumented immigrants were deported in 2012 alone, many the parents of citizen-children with disabilities, according to data from the U.S. Department of Homeland Security [DHS] (Zayas & Bradlee, 2014). This issue is relevant to SVRAs in several ways: (1) the issue of deportation may bring to light the need to address and confirm permanent residency status of foreign-born prospects for vocational rehabilitation services; (2) uncommon counseling and guidance services may be requested by immigrant consumers dealing with family members who have been deported; and (3) cultural and linguistic issues continue to impact ethnic-minority groups, an attempt to understand their dynamics from a non-western perspective within the context of disability may pose significant challenges for immigrant consumers and SVRA practitioners.

What is apparent is the uncompromising realization that this modern demographic landscape dynamized by the increase of ethnic-minority groups in the U.S., particularly new U.S. Citizens and legalized permanent residents with disabilities, has been followed by notice of the need to provide protracted services to them (Bennett et al., 2012; Cross et al., 2015; Leahy et al., 2014; Markides & Rote, 2014). SVRAs will need to prepare to contend with related phenomena in the face of unemployment and under-employment difficulties that persons with disabilities currently encounter (Leahy et al., 2014).

While it is deemed beneficial and desirable for rehabilitation counselors to be familiar with a finite knowledge about the cultural norms of every minority consumer (i.e., immigrant and U.S. born) that he/she serves, the 38th Institute on Rehabilitation

Issues (IRI) Prime Study Group encourages them to adopt the more pragmatic cultural humility approach (IRI, 2015). In the cultural humility approach, "the goal is not to master a finite body of knowledge but to simultaneously look inward to examine one's own conscious and unconscious biases, to reach outward to build relationships with individuals and communities, and to see the client as the expert" (Tervalon & Murray-Garcia, 1998, p. 117). As the percentage of African American or Black, American Indian or Alaska Native, Asian, and Latino applicants increases, so will the demand for counselors who can embrace the cultural humility model in an effort to assist consumers to integrate into the competitive labor market. To this end, there will be a need for new policy initiatives and strategies that will assist SVRAs' rapid response to projected trends for this target population. For example, new strategic plans that encourage staff and leadership trainings on the cultural humility approach could be beneficial. Such trainings could be carried out by Technical Assistance and Continuing Education centers located in RSA regions with heavy minority populations and significant immigration trends.

5. Limitations

This study has three inherent limitations. First, the findings are limited in that they do not specifically forecast the number of new immigrants from racial and ethnic minorities who are projected to apply for SVRA sponsored services. Instead, the findings included minority immigrants as well as U.S. born minorities. The RSA-911 database does not capture or include information in case records as to whether an applicant is an immigrant, and so we cannot ascertain or project numbers specific to immigration status. RSA should consider adding a variable to the case service report inclusive of immigration status information. Second, due to the quantitative nature of the research, no information pertaining to the types of service and policy implications needed in response to the projections is available. Consequently, there is a need to ascertain the perspectives of SVRA personnel and other immigration experts as to the potential implications and responses to this growing crisis. In doing so, the following research questions should be addressed: (a) What is the priority of importance for impacts of emerging and new U.S. citizen and permanent residency population trends on SVRAs' capacity to serve immigrants with disabilities from tradition-

ally underserved racial and ethnic populations? (b) What is the priority of significance for strategies that could be implemented by SVRAs to address micro and macro level impacts of emerging and new immigration trends on service capacity to new U.S. citizens and legal permanent residents from racial and ethnic populations?, and (c) What are the strategies used by states that are successfully meeting the needs of new immigrants and other traditionally underserved racial and ethnic populations?

Third, information contained in the RSA-911 database is not immune to personnel error. Consequently, the database may include erroneous information. The database, nonetheless, is historically accepted as a viable data source for addressing service and policy questions that need to be answered. As a broad generalization, these conclusions may be helpful to national policymakers and state VR agency leaders interested in improving the rehabilitation experiences of minorities.

6. Conclusion

This study assessed the predictive accuracy of select forecast models in regard to the impacts of immigration trends on SVRA application rates. The MGM was demonstrated to be superior to the VAR model. The MGM three-year forecast projected an upward curve trend trajectory in the percentage of new Black or African American, American Indian or Alaskan Natives, Asians, and Latino applicants for FYs 2015 thru 2017. These findings suggest that the MGM represents a promising forecast approach that could assist SVRAs in responding rapidly and appropriately to potential immigration trends impacts. Moreover, projected application percentage curve trends suggest that SVRAs should prepare and plan to serve individuals with disabilities from these minority groups. However, there remains a need for additional demonstration trials to either confirm or refute the MGM's efficacy in prediction accuracy in comparison to other multivariate forecast models.

for Community Living (ACL), Department of Health and Human Services (HHS). The contents of this article do not necessarily represent the policy of NIDILRR, ACL, HHS, and one should not assume endorsement by the federal government.

Conflict of interest

The authors have no conflict of interest to report.

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