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A multivariate time series approach to modeling and forecasting demand in the emergency department ☆

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ABSTRACT

Study objective: The goals of this investigation were to study the temporal relationships between the demands for key resources in the emergency department (ED) and the inpatient hospital, and to develop multivariate forecasting models.

Methods: Hourly data were collected from three diverse hospitals for the year 2006. Descriptive analysis and model fitting were carried out using graphical and multivariate time series methods. Multivariate models were compared to a univariate benchmark model in terms of their ability to provide out-of-sample forecasts of ED census and the demands for diagnostic resources.

Results: Descriptive analyses revealed little temporal interaction between the demand for inpatient resources and the demand for ED resources at the facilities considered. Multivariate models provided more accurate forecasts of ED census and of the demands for diagnostic resources.

Conclusion: Our results suggest that multivariate time series models can be used to reliably forecast ED patient census; however, forecasts of the demands for diagnostic resources were not sufficiently reliable to be useful in the clinical setting.

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1. Introduction

Reports by the General Accounting Office, American College of Emergency Physicians, and the Institute of Medicine (IOM) describe an overburdened United States' emergency care system characterized by overcrowding and patient care delays [1–3]. From 1993 to 2003 emergency department (ED) visits increased by 26% while the number of EDs decreased by 9% [3,4]. These shifts in supply and demand have created an environment in which many EDs regularly operate at or beyond their designed capacity [5]. A 2002 survey commissioned by the American Hospital Association found that approximately two-thirds of all the EDs surveyed believe that they are operating at or above capacity. The same survey found that the perception of overcrowding is positively correlated with the complexity of services the hospital offers and is more prevalent among hospitals in urban settings [6]. In addition to having an adverse impact on patient and clinician satisfaction, ED overcrowding has deleterious effects on the both the quality and timelines of care delivered in the ED [7–11].

The IOM report asserts that crowding problems result from the complex interaction between the demands for and the availability of resources throughout the entire hospital [3,12–24]. Emergency medicine researchers have long believed that surges in the demand for inpatient resources have adverse affects on throughput in the ED [12,13]. An analysis conducted by Rathlev et al. found that increases in hospital occupancy and the number of elective surgical admissions were independently associated with increases in ED patient length of stay [14]. In a similar study, Forster et al. found that hospital occupancy rates exceeding 90% were associated with significant increases in ED patient length of stay, and Asaro et al. concluded that surges in both input, e.g., patient arrivals, and output factors, e.g., the number of patients requiring admission are associated with increases in patient wait times and length of stay in the ED [15,16].

Increasing demand combined with growing scarcity of ED services makes the efficient allocation of ED resources increasingly important. In their report, the IOM recommends that hospitals utilize information technology and use operations research methods to become more efficient [3]. Demand forecasting is one such method, forecasting is a widely applicable, multi-disciplinary science, and is a vital-activity that is used to guide decision making in many areas of economic, industrial, and scientific planning [25]. Modeling and forecasting demand is an active area of inquiry

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among emergency medicine researchers. Models and methods that might be useful for providing decision support in real-time for operational and resource allocation tasks have been of particular interest [26–42]. A variety of different methods have been proposed as viable means of forecasting demand in the ED, some of the proposed methods are: univariate time series modeling, simulation modeling, queueing theory, and machine learning methods [33–39].

The available literature on ED overcrowding consists primarily of descriptive studies that focus on the relationship between inpatient census and ED overcrowding [12–16]. However, many other variables contribute to surges in ED census and ED overcrowding. For instance, the availability of and demand for diagnostic resources, such as laboratory and radiology services are likely to affect ED census. In most cases ED's share diagnostic resources with the rest of the hospital; therefore, it is feasible that external as well as internal demand for shared diagnostic resources have an impact on ED throughput and census. It is our hypothesis that that the demands for resources essential to ED and hospital operations interact dynamically, that is to say, the demands for resources exhibit simultaneous as well as leading and lagging relationships. We could find no literature that described the use of multivariate time series methods to study or forecast demand in the ED. The initial objectives of this paper were to study the temporal dynamics of the demand in the ED, and based on that study; develop multivariate models that can be used to forecast ED census and the demand for critical ED resources.

Our final objective was to explore the potential utility of our multivariate forecasting models to provide decision support in real-time for on-call nurse staffing. The ability to dynamically adjust and allocate staffing resources is likely to grow in importance as regulations requiring hospitals and EDs to adhere to nurse staffing ratios become more common. The most established examples of such government regulations exist in the state of California where hospitals have been required to observe specific patient-to-nurse ratios since 2004 [43]. These regulations are controversial; however, government regulation of patient-to-nurse staffing ratios in other parts of the country is probable and relevant legislation is being proposed on both the state and Federal levels [43–47]. Although nurse staffing ratios remain politically controversial, the scientific evidence is conclusive that these ratios have a significant impact on quality of care, and a robust body of literature has amassed indicating that reductions in the patient-to-nurse ratio are associated with significant reductions in mortality, adverse events, and patient length of stay [48,49].

2. Methods

2.1. Study design

This was a retrospective study using aggregated data for the year 2006 that was extracted from ED information systems. The local institutional review board approved this study and waived the requirement for informed consent.

2.2. Study setting

This study was conducted using data collected from three hospitals operated by Intermountain Healthcare, a nonprofit integrated delivery network that operates hospitals and clinics in Utah and southern Idaho. The three hospitals were chosen because they vary in size and setting and the manner in which the ED interfaces with the rest of the hospital. Table 1 provides descriptive statistics for each hospital, and additional relevant facility characteristics follow.

Table 1
Operational descriptive statistics for three hospitals and hospital emergency departments (ED)

Hospital	Inpatient beds	Trauma designation	Teaching hospital	ED beds (hall beds)	Dedicated laboratory	POCT*	Dedicated radiography	Dedicated radiologist service	Average hospital occupancy (SD)†
1	270	NA	No	27 (5)	No	No	No	Yes	69.08% (15.16%)
2	475	Level I	Yes	25 (7)	No	Yes	Yes	No	81.88% (9.22%)
3	350	Level II	No	28 (4)	Yes	No	Yes	Yes	82.23% (9.59%)

Hospital	Average ED patients per day (SD)	Average ED patient wait time (SD)	Average ED patient LOS (SD)	Admission rate	Average ED patient board time (SD)	Hospital occupancy >90%§
1	144.75 (18.08)	33.78 (26.95)	168.81 (114.47)	9.50%	105.54 (69.22)	5.75%
2	108.20 (12.50)	23.07 (17.23)	183.47 (106.07)	21.20%	77.86 (54.88)	21.37%
3	120.60 (16.50)	50.24 (41.56)	185.38 (112.97)	14.50%	109.48 (97.88)	25.48%

* Point of care laboratory testing.
† Average midday (12 pm) inpatient hospital occupancy during 2006.
§ Percent of time midday census exceeded 90% during 2006.

The ED at Hospital 1 is not equipped with dedicated imaging equipment, and patients requiring radiography and computed tomography (CT) scanning are taken to an adjacent radiology suite, while the EDs at Hospitals 2 and 3 both have dedicated radiography and CT equipment. At Hospitals 1 and 3 a single radiologist is dedicated to reviewing all radiology images from the ED during business hours, while at Hospital 2 radiologist coverage is allocated by modality rather than by hospital department. Each hospital is equipped with digital picture archiving and communication systems (PACS) (IMPAX RIS, AGFA Corporation, Ridgefield, NJ). The three EDs differ in how they interface with their respective hospital's central laboratory. At Hospital 1, all laboratory tests from the ED are sent to the hospital's central laboratory for analysis via pneumatic tube. At Hospital 2, the ED is equipped for point of care testing (i-STAT®, Abbott Point of Care Inc., East Windsor, NJ) for several laboratory tests, including blood gases, electrolytes, chemistries, and cardiac markers; however, administrative reports indicate that point of care testing only accounts for a small portion of the EDs total laboratory volumes (5–10%), and the majority of samples are still processed by the hospital's central laboratory. At Hospital 3, the majority of ED laboratory work is handled by the "STAT" laboratory which is located in the ED. Each ED is equipped with an electronic patient tracking system developed by Intermountain Healthcare. The system serves as the primary communication tool, and tracks many aspects of each patient visit, including the patient arrival/departure time and the time at which orders were made, collected, and completed. All relevant data for the calendar year 2006 were included in the analysis.

2.3. Data collection and processing

Data for this analysis were extracted from Intermountain Healthcare's Oracle based electronic data warehouse. Aggregated hourly data were extracted via SQL queries. Measures of census were collected for each hour. ED patient census was represented as the count of patients either waiting for or receiving treatment in the ED. Inpatient census was defined as the number of patients occupying an inpatient bed. Demand for laboratory resources was measured as the number of laboratory batteries (e.g., complete blood count) that were collected during a given hour (e.g., 12:00:00–12:59:59). Preliminary analysis indicated that 26 common laboratory batteries (Appendix A) accounted for approximately 80% of the laboratory volumes at the EDs included in this analysis. In order to better study the impact of inpatient demand on ED demand we determined that it would be most appropriate to limit our analysis to a core set of laboratory tests for which a significant increase in demand internally or externally could have deleterious effects on ED operations. Therefore, only this core set of 26 laboratory batteries was included in our counts of ED and inpatient laboratory volumes. Similar rationale led us to focus our analysis on the demand for radiography and CT, as these two modalities accounted for almost 90% of the demand for radiology services at the EDs studied. We collected the number of radiography and CT scanning orders for each hour from the ED and inpatient hospital. Additional variables collected include hourly counts of patient arrivals. All variables collected and included in our analysis are summarized in Table 2.

2.4. Outcome measures

Out-of-sample forecast accuracy was assessed for forecast horizons ranging from one to 24 h in advance by calculating the mean absolute error (MAE). The MAE is a frequently used and intuitive measure of forecast accuracy that measures the magnitude of the deviation between the predicted and observed values of a given time series. [25,50] For a series of predicted values $(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n)$ and the corresponding series of observed values $(y_1, y_2, \ldots, y_n)$

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} |(y_t - \hat{y}_t)|. \tag{1}$$

2.5. Primary data analysis

As stated in the introduction, the purpose of this study was twofold. Our first objective was to carry out descriptive analyses of the relationships between the demand for inpatient and ED resources at three local hospitals, and our second objective was to capitalize on the knowledge gained through these analyses by developing multivariate models that could be used to generate forecasts of demand in the ED.

2.6. Descriptive analysis

Prior to the analysis, the data for each facility were split into two sets, the first 7920 h (330 days) of data were allotted for analysis, data description and model fitting, and the final 840 h (35 days) of data were held out to validate our models. We settled on this ratio of approximately 10:1 for the test and validation sets because it allowed us to use the majority of the data for model fitting but still left a sufficient dataset to validate our models. Initial descriptive analyses of the test data were conducted via the visual analysis of time plots, autocorrelation function (acf) plots, and bivariate cross-correlation function (ccf) plots. The acf plots provided a graphical representation of the autocorrelation structure of the time series variables. The acf plots can be used to determine to what extent and magnitude past values of a given time series are related to future values of the same time series. The acf plots provided insight into how reliable past values would be for predicting future values. ccf plots provided similar graphical representations; however, the ccf plots allowed us to study the temporal relationships between pairs of time series variables; thus, ccf plots were useful for identifying leading indicators [25]. Initial analysis of the acf plots indicated that demand in the ED and in the inpatient hospital is characterized by daily, weekly, and annual seasonal pat-

Table 2
Time series variables collected for analysis and inclusion in multivariate forecasting models

Variable	Definition
ED arrivals	Count of patients arriving to the ED during a given hour
ED census	Count of patients waiting for or receiving service in the ED on the hour
ED laboratory orders	Count of laboratory batteries ordered in the ED during a given hour
ED radiography orders	Count of radiography orders made in the ED during a given hour
ED computed tomography (CT) orders	Count of CT orders made in the ED during a given hour
Inpatient census	Count of patients occupying an inpatient bed on the hour
Inpatient laboratory orders	Count of laboratory batteries ordered in the inpatient hospital during a given hour
Inpatient radiography orders	Count of radiography orders made in the inpatient hospital during a given hour
Inpatient CT orders	Count of CT orders made in the inpatient hospital during a given hour

terns as well as by autocorrelation. These same characteristics have been identified in several other studies [27–36,51]. These features of our data signaled that we needed to exercise particular caution when analyzing the ccf plots for leading indicators, because seasonality and autocorrelation convolute cross-correlation analyses and can lead to the identification of spurious relationships [25,52]. To avoid the identification of misleading temporal relationships we applied a series of data transformations to "prewhiten" our data. The primary objective of the prewhitening process was to remove the features (seasonality and autocorrelation) that could potentially confound our cross-correlation analyses. The prewhitening process consisted of two steps. The first step removed the seasonal component of our data by subtracting the mean value for the corresponding hour of the week from the observed value for that hour of the week. The second step removed autocorrelation by fitting an autoregressive model of a common order (4) to each time series, and then used the residuals to perform the cross-correlation analyses [25].

To further evaluate which variables provided predictive value as leading indicators, we employed the method of Granger-causality. The Granger-causality test is a statistical method for determining whether or not one time series is predictive of another. A time series variable, X, is said to "Granger-cause" another time series variable, Y, if it can be demonstrated that lagged values of X provide significant information about future values of Y. While the Granger-causality test does not actually indicate true causality, it has been adopted as a standard methodology for identifying leading indicators [53,54].

After the completion of our descriptive analysis forecasting models were developed using vector autoregression (VAR). VAR models provide a flexible means to model and forecast multivariate time series [25,54–57]. VAR models were originally proposed as a means to study the interrelation of various macroeconomic phenomena, and are essentially a multivariate extension of univariate autoregression models [57]. A univariate autoregression model uses a single equation to expresses the relationship between future values of a given time series and past values of that same time series, while a VAR model is an n-equation n-variable linear model that relates each variable to past values of itself as well as to past values of the other $n-1$ variables [54]. The primary motivation for choosing a multivariate, multiple equation forecasting method was our belief that the demands for ED resources are likely to interact dynamically through time as part of a "closed-loop" system. A basic assumption of the single equation regression model is that the explanatory and response variables constitute an "open-loop" system, where the explanatory variables are believed to affect the response variable, but the response variable does not affect the explanatory variables [25]. We did not believe that this would be the case in modeling the demands for ED resources. An example of the "closed-loop" nature of demand in the ED is when a surge in ED census is followed by a surge in laboratory volumes which leads to another unexpected increase in ED census. The underlying causal mechanism for the secondary surge in ED census is increased ED length of stay caused by increased laboratory turnaround times.

Initially hourly ED census, laboratory, radiography, and CT volumes as well as inpatient census, laboratory, radiography, and CT volumes were included as endogenous variables in a reduced form seasonal VAR model. Then the hourly ED patient arrival count was added to the model as exogenous variable. model parameters were estimated by ordinary least squares, and daily and weekly seasonality were accounted for by the incorporation dummy variables that represented the hour of the day and day of the week. The autoregressive order of the VAR model was determined via the minimization of the Akaike information criterion (AIC) [58].

2.7. Model validation and forecasting

Our primary objective was to evaluate the validity of our models in terms of their ability to provide accurate post-sample forecasts of census and of the demand for diagnostic resources in the ED. This was accomplished through a simulated post-sample forecasting scenario in which we incrementally expanded the training set by 1 h and then generated forecasts for all endogenous variables for horizons ranging from one to 24 h ahead. This procedure enabled us to generate one to 24 h ahead forecasts for all 840 h in the validation set. We evaluated the forecast accuracy of our models by computing the MAE for each forecast horizon (1–24 h). We compared the forecast accuracy achieved using the VAR models to a benchmark univariate forecasting method. The benchmark method chosen was seasonal Holt-Winters exponential smoothing. Exponential smoothing is one of the most prevalent forecasting methods and based on its success and frequent use we felt that it provided a fair benchmark [25].

Our final objective was to explore the potential utility of our multivariate forecasting models to provide decision support in real-time for operational and resource allocation tasks. In order to do this we evaluated the discriminatory power of the output from our forecasting models in predicting instances when acceptable patient-to-nurse ratios would be surpassed. We used the four to one ED patient to ED nurse ratio that is mandated by the state of California as our reference standard of an acceptable patient-to-nurse ratio. We defined any instance where the observed ED census exceeded the expected ED census by four or more patients (i.e., the ED is understaffed by a full nurse) as an instance of understaffing. We determined that in these cases it would be useful to have advanced warning that would enable an additional RN to be contacted prior to the acceptable patient-to-nurse-ratio being surpassed. In order to do this we entered the forecasted deviation from the expected ED census (forecasted ED census − ED expected census) for forecasts made 1–12 h in advance into a single variable logistic regression model. The discriminatory power of the single variable logistic regression models based on the forecasted deviation to predict instances of understaffing was assessed via the empirical calculation of the full area under the receiver operating characteristic curve (AROC) for each forecast horizon. All statistical analyses including the forecasting model development and evaluation were performed using the *R* statistical software package (V.2.5.1) [59].

3. Results

3.1. Descriptive results

Differences in setting, resources, and the manner in which the three EDs interface with the inpatient hospital led to slight differences in terms of parameter estimates; however, the conclusions drawn from our descriptive analyses were consistent across the three facilities. Therefore, in order to be concise we only present the results of our descriptive analysis for one hospital, Hospital 1. However, we do report the results of our model validation for all three hospitals.

The autocorrelation function plots for ED census, laboratory, radiography, and CT volumes are presented in Fig. 1. ED census exhibits a highly persistent autocorrelation structure, with statistically significant autocorrelation still present at lags up to 12 h. The demand for ED resources exhibit much less autocorrelation than ED census, this result suggests that past values of ED census will be highly useful in predicting future ED census while the demand for ED resources in the past is less likely to be indicative of future demand. Fig. 2 presents the autocorrelation function plots for inpatient census and laboratory, radiography,

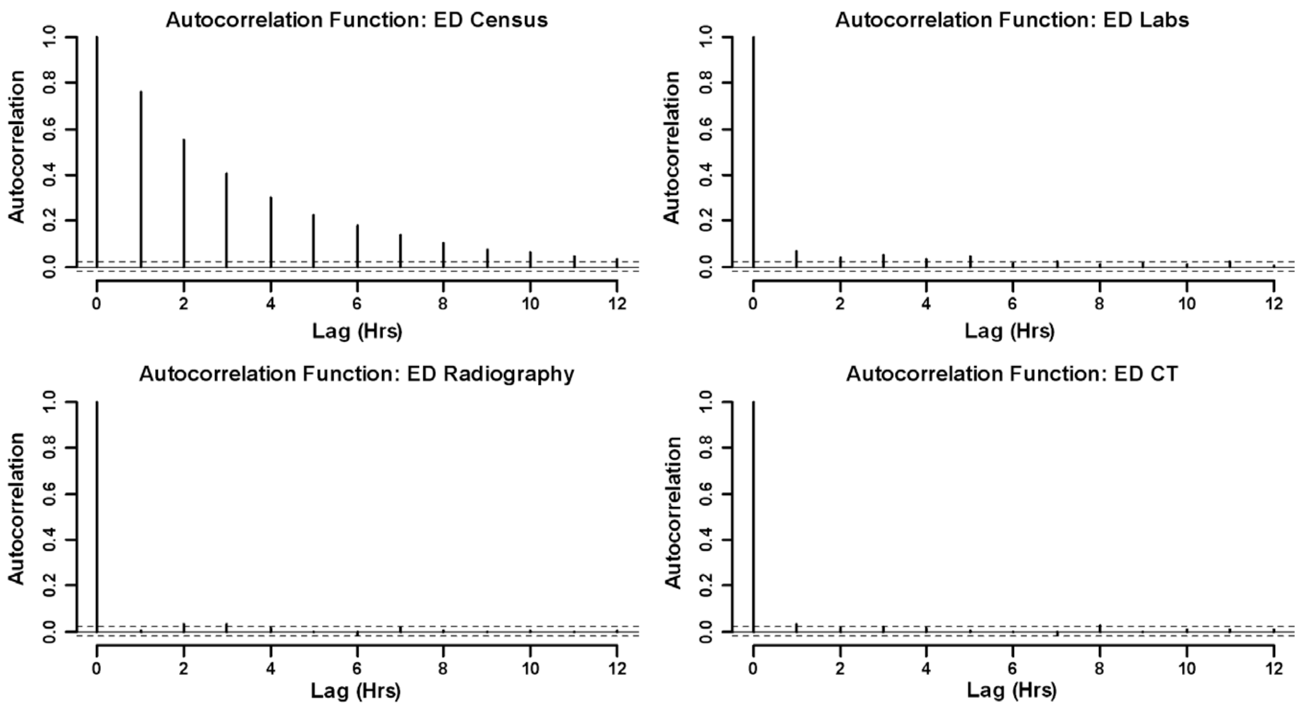

Fig. 1. Autocorrelation function plots for deseasonalized hourly ED patient census, laboratory, radiography, and computed tomography (CT) volumes for the ED at Hospital 1. The autocorrelation function plot depicts the extent and magnitude of the correlation between current values of a time series variable and its own past values. The dashed lines indicate statistical significance ($p \leqslant 0.05$).

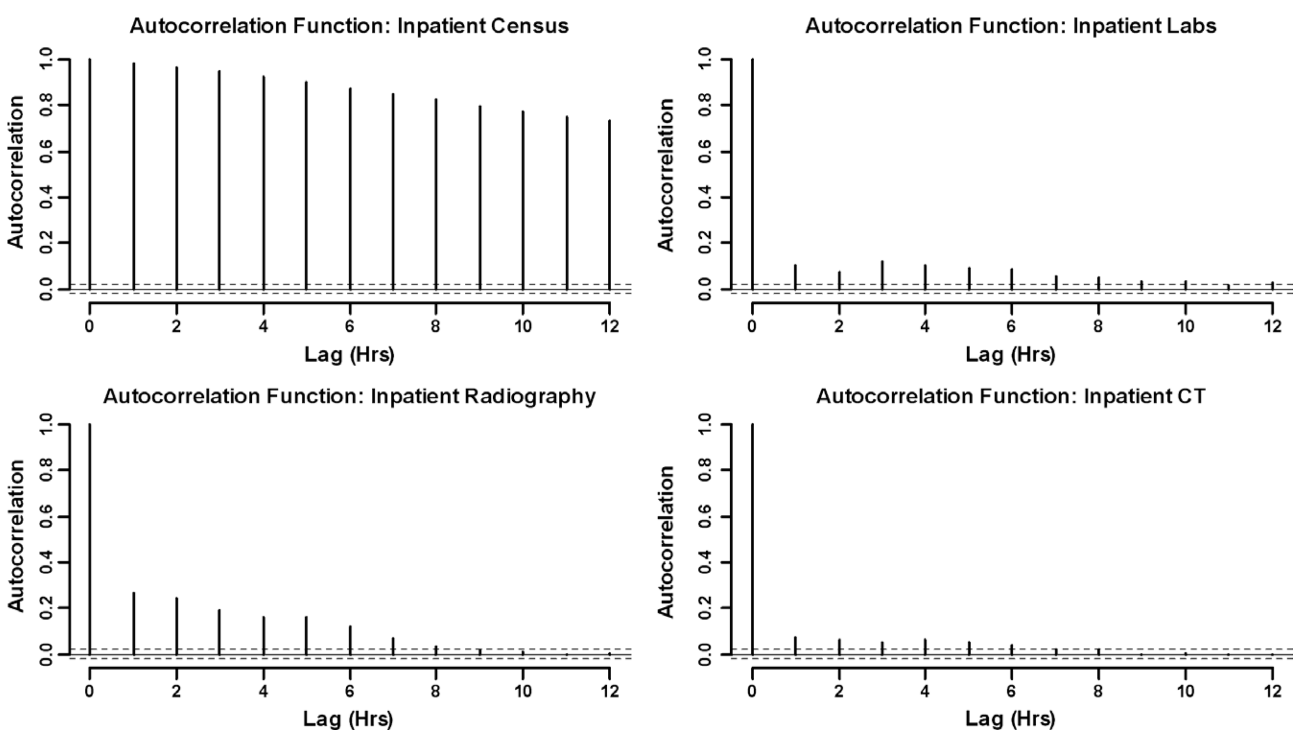

Fig. 2. Autocorrelation function plots for deseasonalized hourly inpatient census, laboratory, radiography, and computed tomography (CT) volumes for Hospital 1. The autocorrelation function plot depicts the extent and magnitude of the correlation between current values of a time series variable and its own past values. The dashed lines indicate statistical significance ($p \leqslant 0.05$).

and CT volumes. Like ED census, inpatient census is highly autocorrelated, however unlike the ED, demand for laboratory, and radiography resources display signs of persistent autocorrelation in the inpatient setting.

Fig. 3 presents the bivariate cross-correlation relationships between ED patient arrivals and ED census, laboratory, radiography, and CT volumes. As expected, Fig. 3 indicates that patient arrivals lead demand for all ED resources. ED arrivals are a strong leading

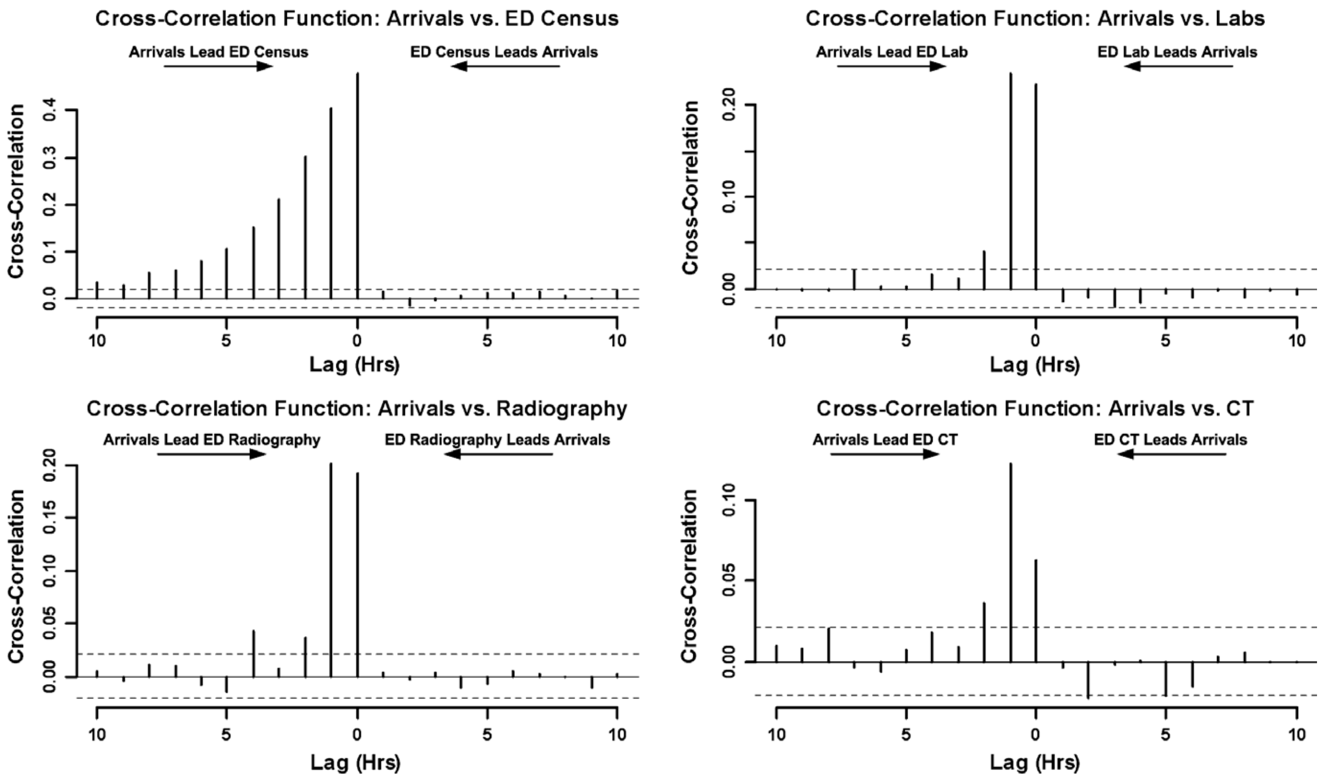

Fig. 3. Cross-correlation function plots for hourly ED patient arrivals vs: ED census, laboratory, radiography, and computed tomography (CT) volumes at Hospital 1. Reading left to right evaluates ED arrivals as leading indicator of the four markers of demand in the ED listed above, and reading from right to left evaluates the listed markers of demand as leading indicators of ED arrivals. As expected these figures indicate that ED arrivals lead the demand for various ED resources and that the demand for ED resources is not indicative of future ED patient arrivals at Hospital 1.

indicator of ED census and as the first plot in Fig. 3 suggests ED arrivals may be predictive of future ED census up to 10 h in advance. The cross-correlation plots in Fig. 3 also suggest a simultaneous relationship between arrivals and demand for diagnostic resources, i.e., a significant portion of diagnostic orders are made during the hour of arrival. However, the plots also suggest that arrivals from in the previous 2 h are also correlated with laboratory, radiography, and CT volumes in the current hour. This indicates that arrivals are likely to be useful in making short-run forecasts of the demand for diagnostic resources in the ED. Fig. 4 presents the cross-correlation function plots for ED arrivals and inpatient census, laboratory, radiography, and CT volumes. Other than a statistically significant (albeit relatively small) simultaneous correlation between ED arrivals and inpatient census, there is little indication that ED arrivals will be useful as a leading indicator of inpatient demand. Fig. 5 presents the cross-correlation function plots for ED census and laboratory, radiography, and CT volumes. Fig. 5 indicates that ED census leads demand for ED resources and inpatient admissions, and the non-zero cross-correlations on either side of lag zero suggests that feedback exists between ED census and the demand for diagnostic resources. The presence of feedback suggests a "closed-loop" system in which the variables interact dynamically. The existence of feedback relationships provides justification of our choice of a multi-equation modeling strategy because multiple regression, transfer-function, and univariate time series models are not able to account for feedback [25].

Fig. 6 presents the cross-correlation function plots for ED census and four markers of inpatient demand. Given reports in the existing literature, our hypothesis was that we would observe significant temporal relationships between ED census and inpatient demand, however Fig. 6 suggests otherwise, and indicates that inpatient markers of demand are unlikely to be useful in predicting ED census. Conversely, ED census is unlikely to be predictive of inpatient demand at the hospitals studied. Finally, Fig. 7 presents the cross-correlation function plots representing the temporal relationships between the demands for diagnostic resources in the ED. These plots indicate simultaneous relationships between laboratory, radiography, and CT volumes, implying that surges in demand for resources (e.g., laboratory, radiography, and ct) tend to happen simultaneously, and are likely to be proceeded by a surge in patient arrivals. However, the ccf plots also indicate that laboratory volumes might be useful in predicting CT volumes 1–2 h ahead, and to a lesser extent predicting radiography volumes in the subsequent hour.

We followed up the cross-correlation analyses up with Granger-causality tests, and Table 3 reports the results of these tests. The authors recognize the problematic nature of conducting and reporting the *p*-values for a large number of hypothesis tests as is done in Table 3. However, Table 3 is used more as a vehicle to verify the results of our cross-correlation analyses rather than to assign statistical significance to those relationships. Table 3 supports the conclusions that we were able to draw from the cross-correlation analyses. The Granger-causality test provided additional evidence of a "closed-loop" system, as Table 3 indicates that ED census both leads and is led by the demand for laboratory and CT resources. Additionally, the Granger-causality analyses corroborate our conclusion that the demands for inpatient resources are not likely to be useful as leading indicators of ED census or any other marker of demand in the ED.

In its reduced form, a VAR model is simply a collection of multivariable linear regression models. The regression parameter estimates along with their accompanying standard errors and p-values for the first four equations of the VAR model (i.e., the equations for ED census, ED laboratory, ED radiography, and ED CT volumes) for

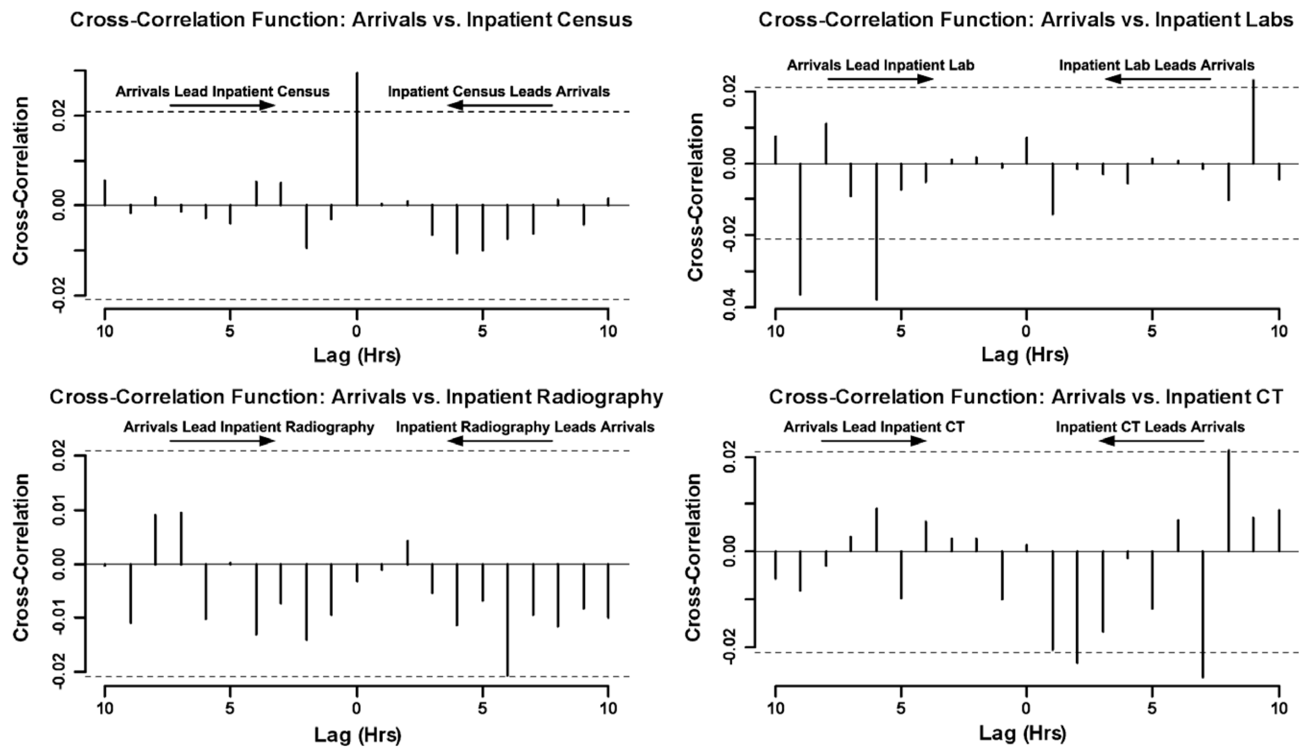

Fig. 4. Cross-correlation function plots for hourly ED patient arrivals vs: inpatient census, laboratory, radiography, and computed tomography (CT) volumes at Hospital 1. Reading left to right evaluates ED arrivals as leading indicator of the four markers of demand listed above, and reading from right to left evaluates the listed markers of demand as leading indicators of ED arrivals. These figures indicate that ED arrivals are not likely to be useful in predicting future demand for ED resources at Hospital 1.

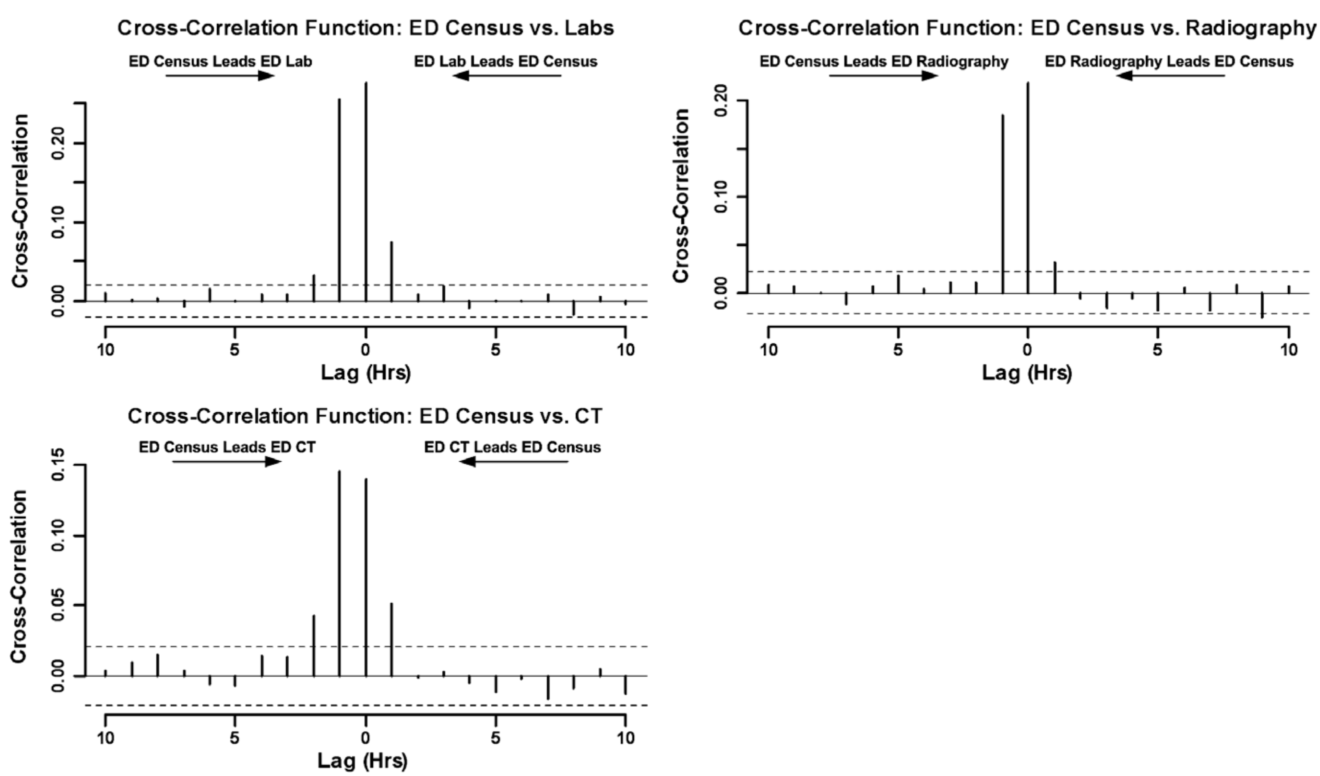

Fig. 5. Cross-correlation function plots for hourly ED census vs: ED laboratory, radiography, and computed tomography (CT) volumes at Hospital 1. Reading left to right evaluates ED census as leading indicator of the three markers of demand in the ED listed above, and reading from right to left evaluates the listed markers of demand as leading indicators of ED census. Significant cross-correlations on either side of lag zero indicates that feedback exists between ED census and demand for various ED resources.

Hospital 1 are included as an appendix (Appendix B). Analysis of the estimated coefficients largely confirms what we were able to ascertain from our other descriptive analyses, that is to say, demand fluctuates based on the time of day and day of the week

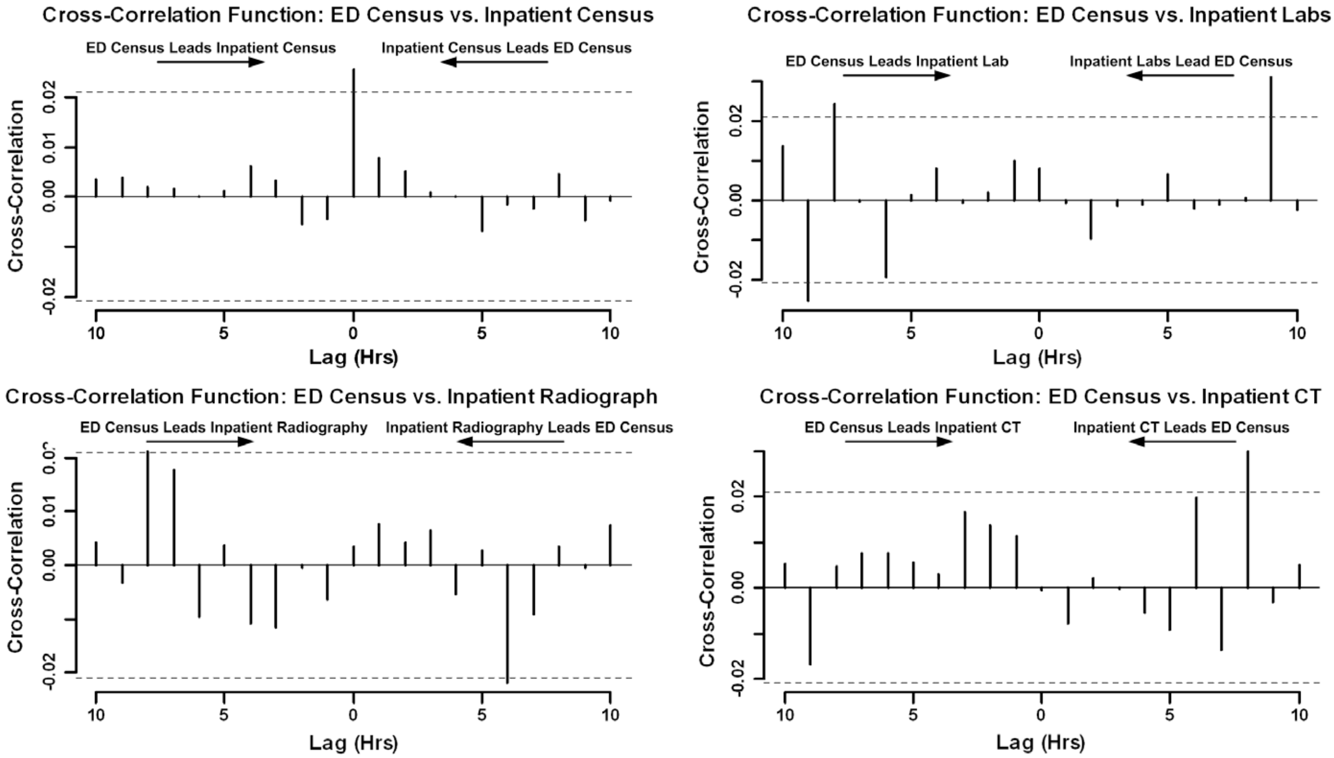

Fig. 6. Cross-correlation function plots for hourly ED census vs: inpatient census, laboratory, radiography, and computed tomography (CT) volumes at Hospital 1. Reading left to right evaluates ED census as leading indicator of the four markers of demand listed above, and reading from right to left evaluates the listed markers of demand as leading indicators of ED census. These figures indicate that markers of inpatient demand are not likely to be useful in predicting future demand for ED census and vice versa at Hospital 1.

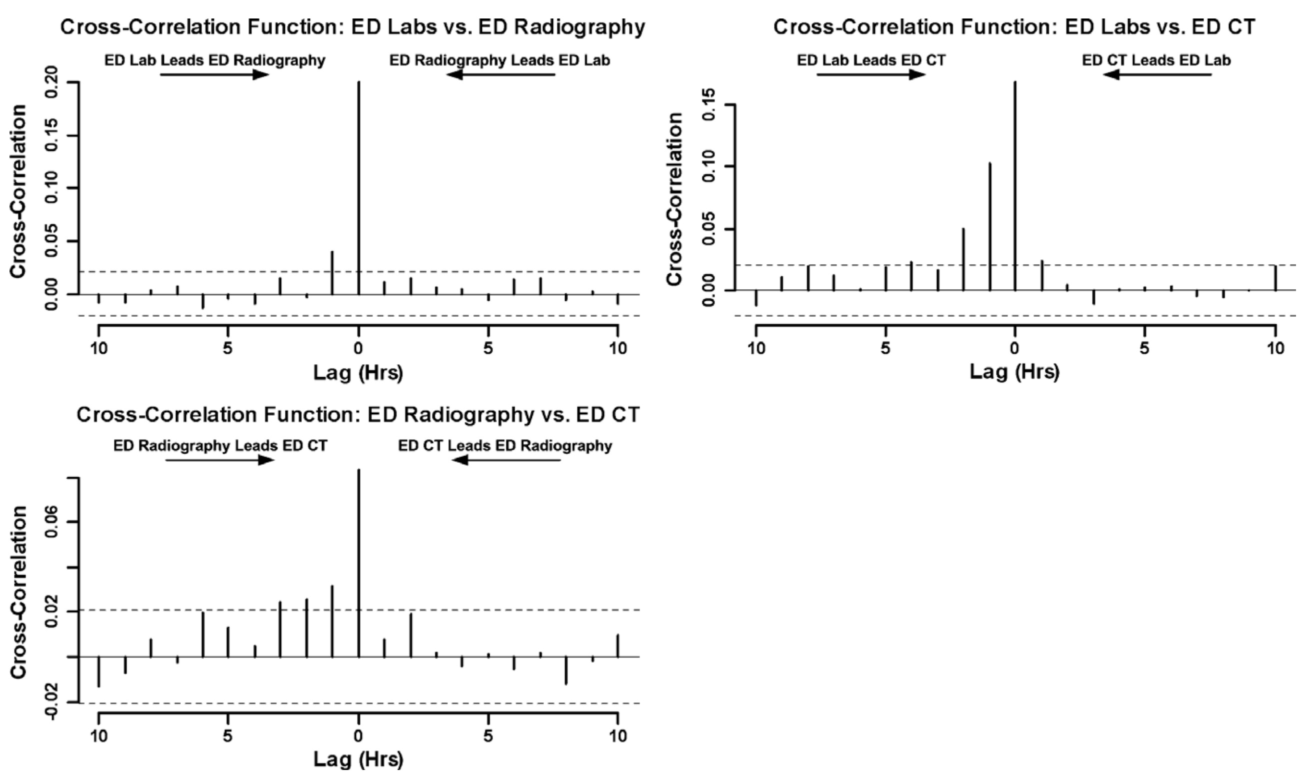

Fig. 7. Cross-correlation function plots for hourly ED laboratory vs. ED radiography volumes, and ED laboratory vs. ED computed tomography (CT) volumes, as well as ED radiography vs. ED CT volumes at Hospital 1. These figures indicate leading and simultaneous relationships between demand for laboratory and radiology resources in the ED at Hospital 1.

and is driven by the exogenous patient arrival process. The regression coefficients also confirm that significant internal interaction exists between the demands for ED and inpatient resources; however; there is little evidence that similar external interactions exist.

Table 3
p-Values for bivariate Granger-causality tests conducted using the data from Hospital 1, column labels indicate which variable is being evaluated as a leading indicator (regressor), and row labels indicate which variable is being evaluated as the dependent variable

Dependent variable	Regressor							
	ED Census	ED labs	ED radiography	ED CT	Inpatient census	Inpatient labs	Inpatient radiography	Inpatient CT
ED census	NA	<0.01	0.11	<0.01	0.95	0.94	0.93	0.90
ED laboratories	<0.01	NA	0.39	0.24	0.21	0.09	0.23	0.59
ED radiography	<0.01	<0.01	NA	0.54	0.71	0.37	0.25	0.02
ED CT	<0.01	<0.01	<0.01	NA	0.97	0.89	0.45	0.63
Inpatient census	0.98	0.88	0.16	0.24	NA	0.08	<0.01	0.68
Inpatient laboratory	0.91	0.54	0.96	0.66	<0.01	NA	<0.01	<0.01
Inpatient radiography	0.74	0.98	0.51	0.74	<0.01	<0.01	NA	<0.01
Inpatient CT	0.35	0.11	0.25	0.07	<0.01	<0.01	<0.01	NA

The autoregressive order for each model was determined by the minimization of the AIC. VAR models of autoregressive order eight, seven, and nine were selected for models for Hospitals 1, 2, and 3, respectively. Goodness-of-fit statistics (Table 4) varied between the eight equations of the VAR model, with the multiple correlation coefficient (R^2) ranging from 0.99 for 1 h ahead forecasts of patient ED census to 0.49 for 1 h ahead forecasts of ED CT volumes. Obviously, variables with highly persistent autocorrelation structures such as inpatient and ED census can be predicted with a greater degree of accuracy than variables such as ED CT volumes that exhibit little autocorrelation.

3.2. Forecasting results

Because our descriptive analyses indicated that very little predictive value was likely to be gained by including variables representing inpatient demand in forecasting models for demand in the ED, we decided to fit two VAR models for each Hospital. VAR model 1, or the full model, included both inpatient and ED variables, while VAR model 2 included only ED variables. Both VAR models included ED patient arrivals as an exogenous variable. Each model was capable of generating forecasts only for the endogenous variables included in the model; therefore, VAR model 1 generated forecasts for inpatient as well as ED variables, while VAR model 2 generated forecasts only for ED variables. Since the emphasis of this study is forecasting demand in the ED we only report measures of accuracy for ED variables. The results of our post-sample model validation are presented for each facility in Figs. 8–10. For each figure we present measures of the forecast error (MAE) for forecast horizons ranging from 1 to 24 h ahead for ED census, laboratory, radiography, and CT volumes. Each figure shows the MAE achieved using VAR models 1 and 2 as well as the forecast accuracy using Holt-Winters exponential smoothing. At Hospitals 1 and 2, VAR models 1 and 2 provided more accurate forecasts of demand for all ED variables for forecast horizons up to 24 h ahead when compared to the benchmark univariate forecasting method. At Hospital 3, VAR models 1 and 2 provided better or comparable forecast accuracy for horizons up to 24 h for ED patient census, and for ED laboratory and radiography volumes. We identified very little difference between the forecasting performance of the full model, model 1, and the model that only incorporated ED variables, model 2. This result corroborates what we found during our descriptive analyses, i.e., that little predictive value would be garnered by modeling the interaction between demand in the ED and the inpatient hospital. Fig. 11 presents four separate plots, in the first we see the observed compared to the expected ED census (based on historical averages) for one week (11/26/2006–12/2/2006) at Hospital 2. This figure indicates that in some instances during this particular week (e.g., Thursday and Friday afternoon) there were large deviations (12 patients or more) in the observed ED census from the expected ED census. The three remaining plots in Fig. 11 present the observed ED census compared to the forecasted ED census at 1, 2, and 3 h ahead. These plots indicate that 1 h ahead using model 2 we are able to forecast ED census at a high degree of accuracy, at 2 h ahead our predictions are less accurate but still able to predict significant departures from normal ED census levels, and at 3 h ahead our predictions begin to regress towards the expected ED census. Fig. 12 presents observed, expected, and predicted laboratory volumes in the same way as in Fig. 11 for the same week. Just as was the case with ED census, Fig. 12 exhibit significant variation even after accounting for hourly and weekly cycles. However, unlike ED census our model does not appear to do nearly as well at predicting extreme departures from expected norms even at short forecast horizons.

As mentioned in Section 2, we were interested in evaluating whether the forecasts of ED census generated by our multivariate models could reliably predict instances when it would be necessary to bring in an on-call nurse. The results of this analysis for each ED are presented in Fig. 13, which plots the estimated AROC for instances of understaffing for forecast horizons ranging from 1 to 12 h in advance. ED 1 was "understaffed" at 210 (25%) of the 840 h in the validation set, and the AROC values ranged from 0.90 at a forecast horizon of 1 h to 0.57 at a forecast horizon of 12 h. ED 2 was "understaffed" at 134 h ($\sim$16%) of the validation set, and the AROC values ranged from 0.85 at a forecast horizon of 1 h and 0.55 at a forecast horizon of 12 h. And finally, ED 3 was "understaffed" for 139 h ($\sim$17%) of the validation set, and the AROC values ranged from 0.91 at a forecast horizon of 1 h and 0.50 at a forecast horizon of 12 h.

Table 4
Goodness-of-fit statistics (Multiple R^2) for each endogenous variable included in the eighth order vector autoregression model for Hospital 1

Endogenous variable	Multiple R^2
ED census	0.97
ED laboratory volumes	0.80
ED CT volumes	0.50
ED radiography volumes	0.70
Inpatient census	0.99
Inpatient laboratory volumes	0.91
Inpatient CT volumes	0.71
Inpatient radiography volumes	0.88

3.3. Limitations

This analysis is limited in that it only considered data from three facilities located in the same region of the country. Like most US hospitals, each of these facilities struggles to manage fluctuating demand for its resources; however, it is not typical for them to experience acute shortages and gridlock characterized by symptoms such as ambulance diversion and patients boarding in the ED for extended periods of time that may be more preva-

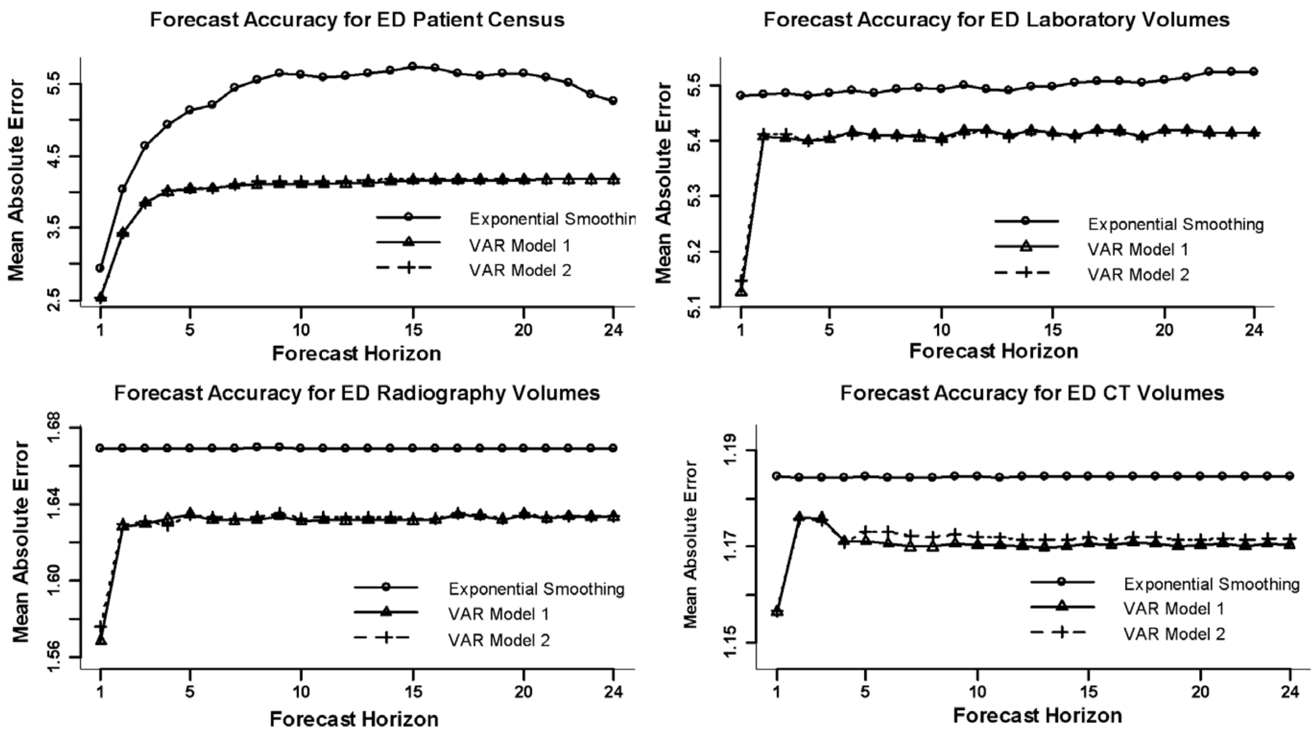

Fig. 8. Graphical assessment of forecast accuracy (mean absolute error) for forecast horizons from 1 to 22 h ahead at Hospital 1 for four markers of demand in the ED.

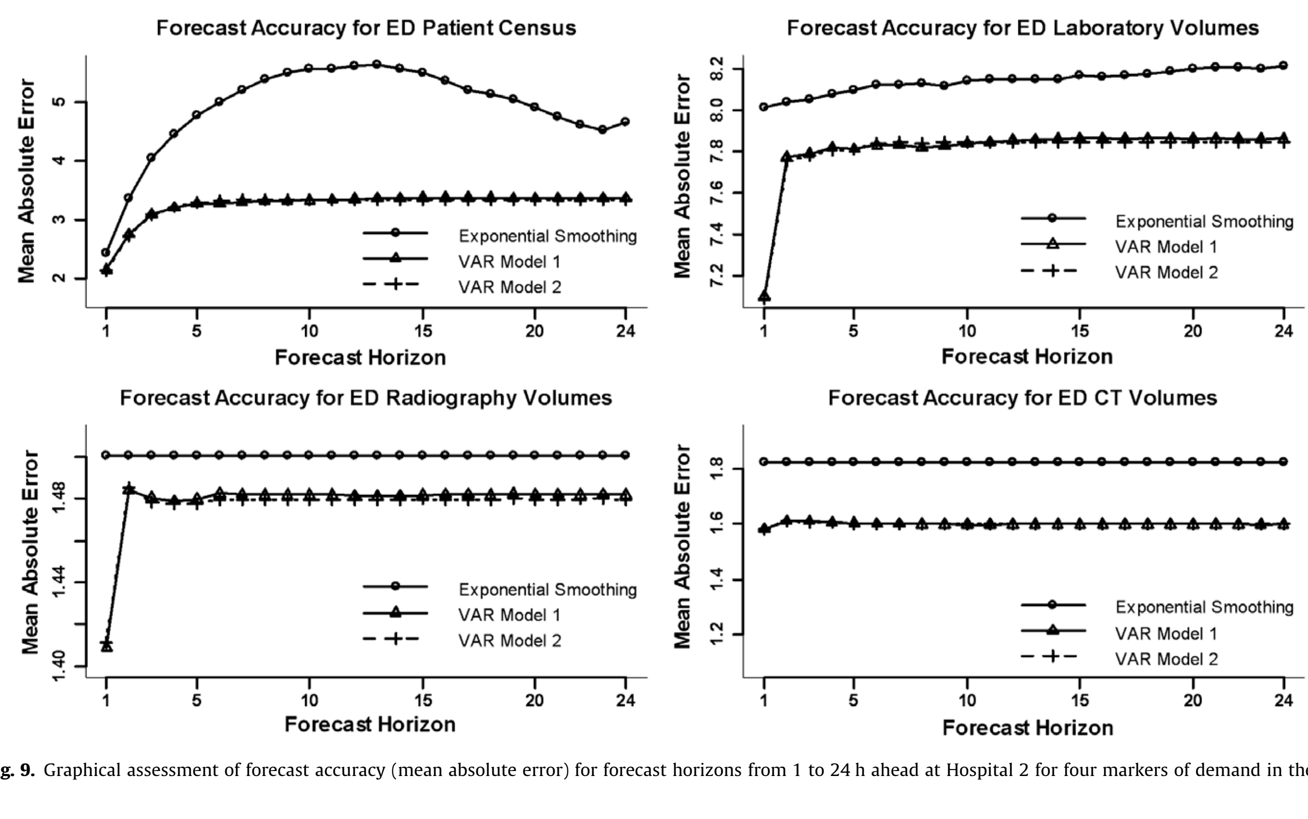

Fig. 9. Graphical assessment of forecast accuracy (mean absolute error) for forecast horizons from 1 to 24 h ahead at Hospital 2 for four markers of demand in the ED.

lent at other institutions or in other regions of the country. For this reason the conclusions drawn from the descriptive portion of our analysis, i.e., that demands for inpatient resources seem to have little predictive value for demand in the ED, may not be generalizable to other institutions. A retrospective design was chosen for this initial analysis because it was the most efficient way to asses the numerical accuracy and predictive ability of our forecasting models. However, the retrospective nature of our analysis was a limitation because it did not allow us to evaluate how clinicians would respond to forecasts in real-time. This is a critical issue and should be a focus of any future work related to real-time demand forecasting in health care environments. An-

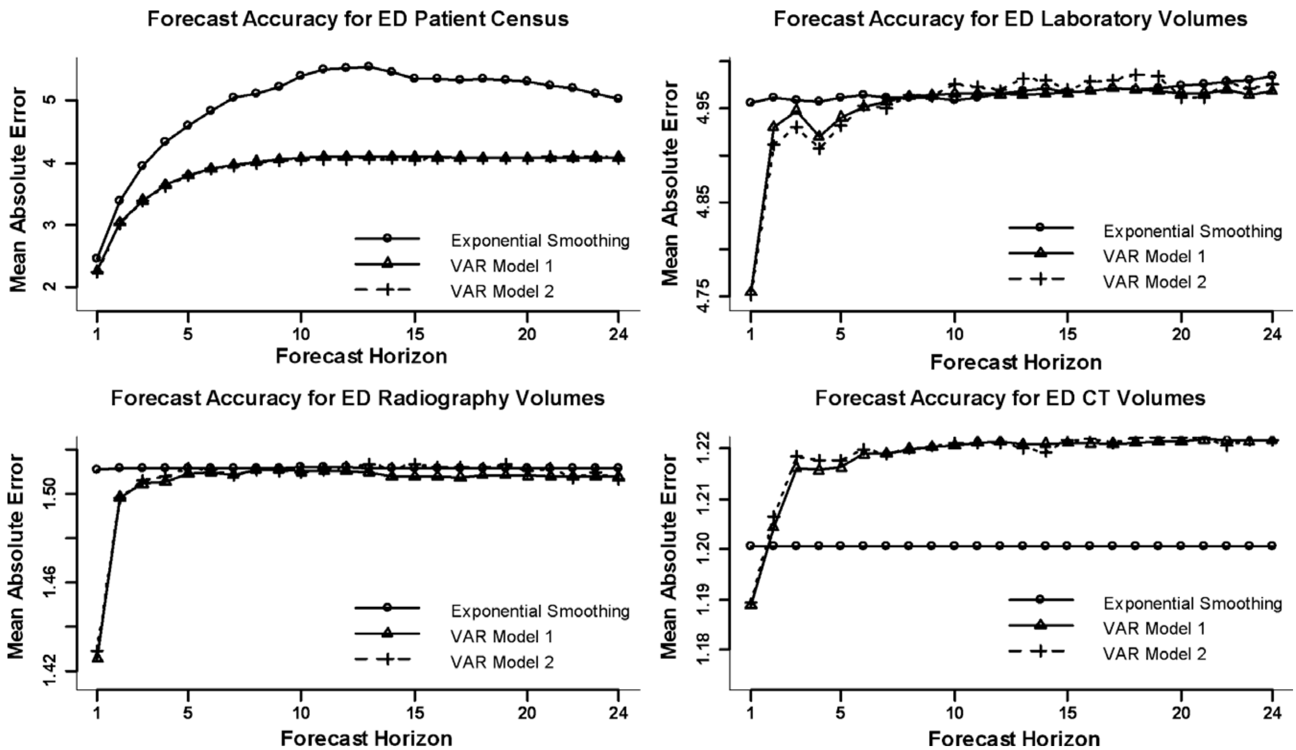

Fig. 10. Graphical assessment of forecast accuracy (mean absolute error) for forecast horizons from 1 to 24 h ahead at Hospital 3 for four markers of demand in the ED.

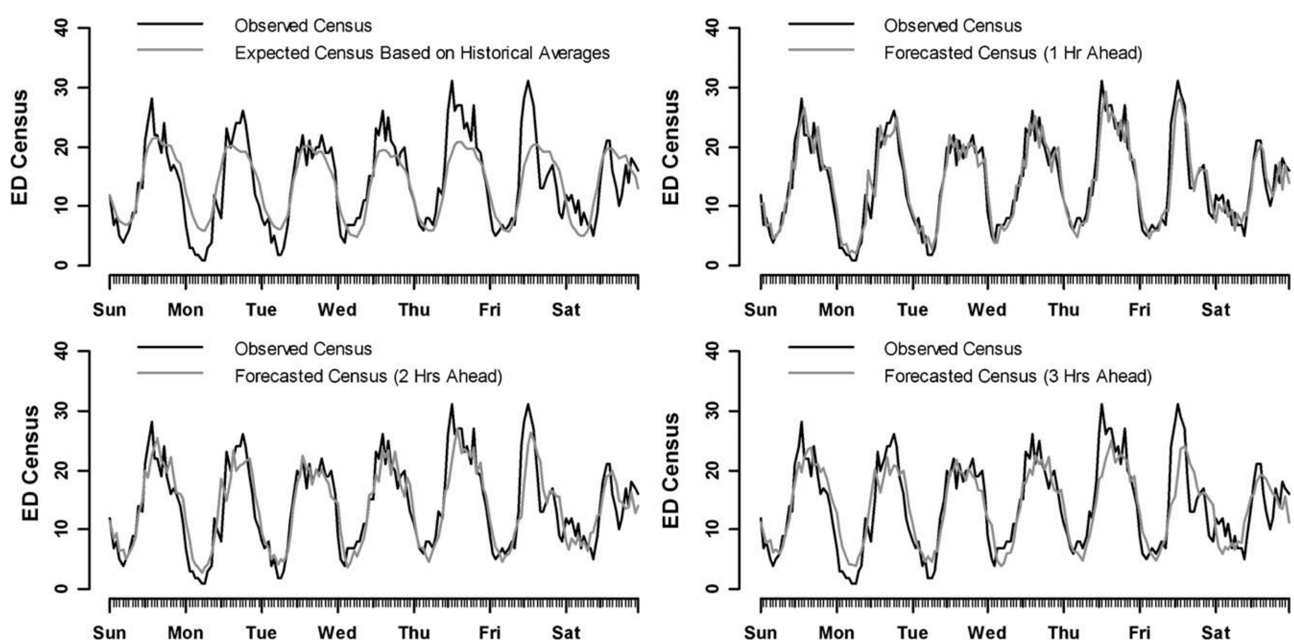

Fig. 11. Observed hourly ED census for the week 11/26/2006–12/2/2006 at Hospital 2 compared to the expected census based on historical averages and compared to forecasted census 1, 2, and 3 h ahead.

other limitation of this analysis pertaining to the utility of our models to provide decision support for on-call nurse staffing is that we do not consider many other factors that are important when making staffing decisions in an ED or any other unit of a hospital (e.g., cost, employee satisfaction, etc.). Finally, our analysis did not account for systematic factors on the community level that are likely to have an effect on crowding levels such as crowding at neighboring hospitals and EDs.

4. Discussion

The results of our descriptive analyses are contrary to much of the existing literature in regards to the impact of inpatient hospital operations on ED operations. Based on the results of previous studies published by other investigators our expectation was to find significant interaction between patterns of demand in the ED and in the inpatient hospital (particularly

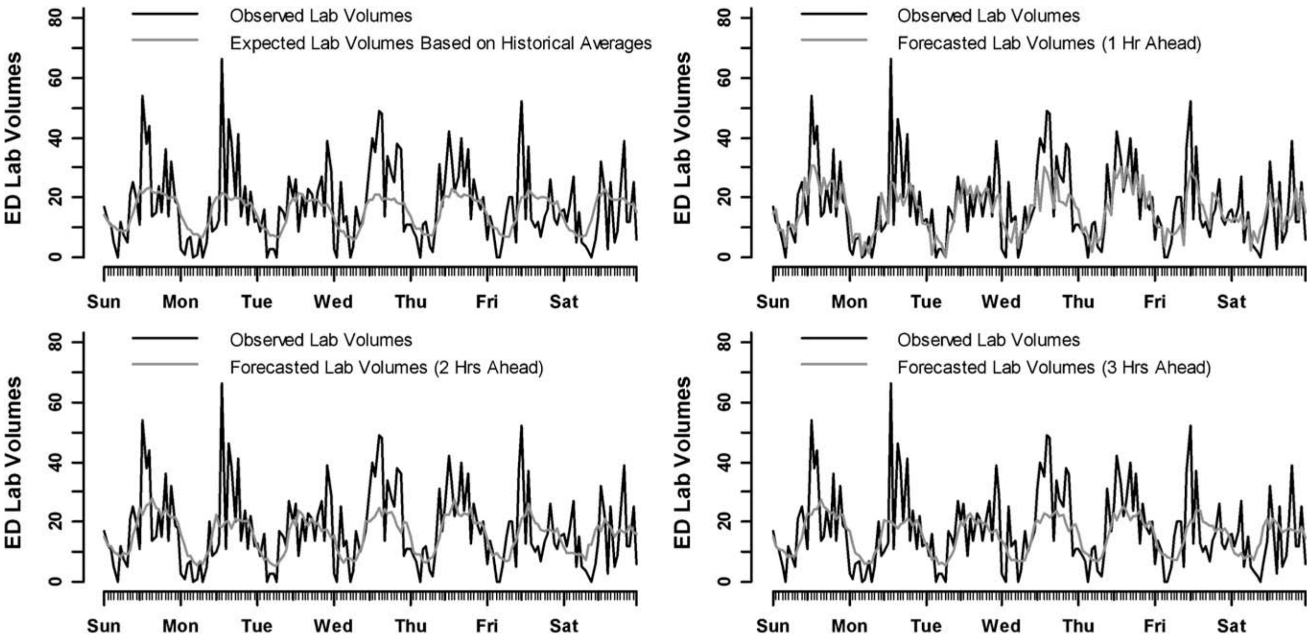

Fig. 12. Observed hourly ED laboratory order volumes for the week 11/26/2006–12/2/2006 at Hospital 2 compared to the expected laboratory order volumes based on historical averages and compared to forecasted laboratory order volumes 1, 2, and 3 h ahead.

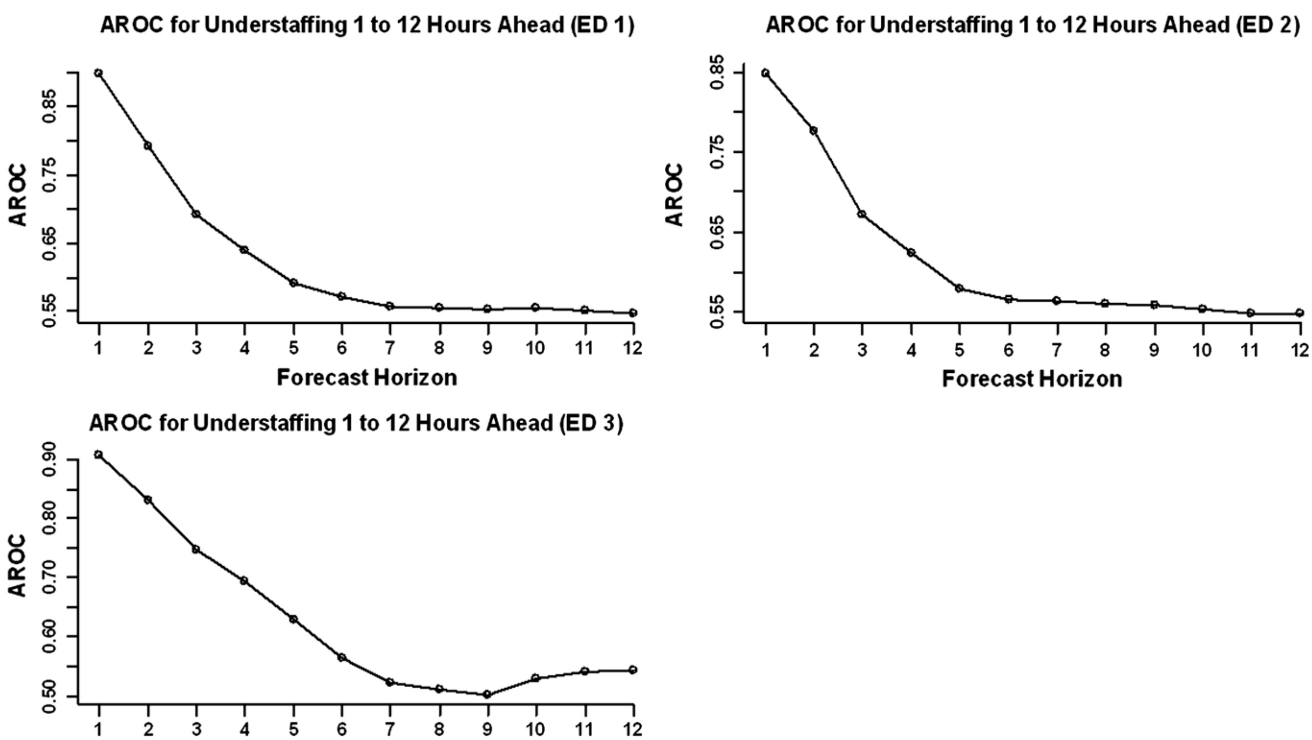

Fig. 13. Area under the receiver operating characteristic curve for predicting instances of understaffing (i.e., observed census exceeds expected census by four or more patients) for forecast horizons from 1 to 12 h in advance.

inpatient census). We believed that studying three diverse EDs that interfaced differently with their respective hospitals would be a particularly effective means for parsing out the impact of inpatient demand on the ED. This was not the case, and we questioned whether our choice of analytical methods might have led to our contrary results. Our analysis focused on high-level aggregates of demand, e.g., hourly laboratory volumes, while previous analyses were typically granular in focus, e.g., individual patient's length of stay [16]. We were concerned that our high-level models were potentially missing important relationships that were detected by more granular analyses at other institutions. Therefore, to be cautious we chose to mimic a previous analysis described in the emergency medicine literature in order see if similar conclusions could be drawn in regards to the relationship between ED and inpatient operations at one of the hospitals considered in our analysis. Asaro et al. used linear regression to evaluate the impact of various system and patient-level variables on patient throughput at a single academic medical center. They report that a shift in inpatient census from the 20th to the 80th percentile resulted in an average increase in length of stay of 19 min for patients requiring admission to the hospital [16]. Using data from Hospital 2, we fit a similar regression model that incorporated similar input and output factors and found that an identical increase in inpatient census (20th to 80th percentile) resulted in an average increase in admitted patient length of stay of only 5.40 min. This result supports the conclusion that at the facilities we considered in our analysis inpatient operations have a much smaller impact on the ED than has been previously reported in the literature, and indicates that our high-level models of aggregate demand seem to capture the reality of the cumulative effects of what is occurring at the individual patient level.

As we acknowledge in Section 3.3, the differences in the results of our descriptive analyses compared to results presented in the literature are likely due to institutional or regional differences. The manner in which hospitals and EDs operate varies widely across the country, and it is unlikely that results drawn studies conducted at a small number of hospitals will be generalizable. Therefore, we advocate a focus on the development and use of robust analytical methods that can be used by individual institutions to study the dynamics of demand locally. We believe that the methods described in this article make an important contribution to the existing literature in this area because they accommodate the analysis of multiple forms of demand in the ED, whereas previous literature has focused primarily on univariate methods for modeling patient census [33,35,47]. We also believe that the methods described can be of general use to hospitals and emergency departments in guiding policy and procedural initiatives to improve operations in the emergency department. For instance, conventional wisdom, the available literature, and to some extent local sentiment indicated that patient flow problems in the ED result from overcrowding in the inpatient hospital [12,13,15]. However, our descriptive analyses indicated that at the EDs we studied inpatient demand appears to have little impact on ED census. On the other hand, we did find that there was significant interaction between ED census and the demands for diagnostic resources. Suggesting that improvement efforts focused on internal operations would be more likely to yield measurable process improvements and reductions in ED overcrowding.

In addition to conducting a thorough descriptive analysis, the development and evaluation of means to forecast ED census and the demand for diagnostic resources were of primary importance. We were partially successful in this endeavor, we were pleased with the high degree of accuracy to which our multivariate models were able to forecast ED census; however, we do not believe that the multivariate VAR models provide sufficiently accurate forecasts of the demand for diagnostic resources to be particularly useful in the clinical setting. This failing is likely due to the fact that the demand for diagnostic resources is primarily driven by the acuity and chief complaints of patients arriving to and being treated in the ED. We found the acuity of patients to be highly unpredictable and therefore the resultant demand for resources was difficult to predict as well.

Our review of the literature identified several studies that propose and or evaluate methods or models to forecast demand (primarily patient census) in a variety of healthcare settings [33,35,39,47,60–67]. To the best of our knowledge, VAR models have not been proposed nor evaluated. To provide context for how accurate our models are relative to methods that have been proposed previously we would like to be able to directly compare our resultant accuracy with that achieved by other investigators. However, the results of published studies are not consistent in how they evaluated their models nor do they consistently report a standard measure of forecast error. Holt-Winters exponential smoothing has been proposed as a methodology for forecasting demand [35], and our results suggest that our multivariate VAR models provide improved short-run forecast accuracy when compared to exponential smoothing models. Other studies have proposed univariate ARIMA models as a means of forecasting ED census [33,39]. We did not evaluate the use of ARIMA models in this study; however, based previous experience working with univariate models in the context of predicting ED census we have found little difference between ARIMA models and exponential smoothing models in terms of forecast accuracy; therefore, we are inclined to believe that our multivariate models would outperform most traditional univariate approaches.

In terms of predicting ED operating conditions, i.e., instances of understaffing our models provided moderate predictive discriminatory power for short forecast horizons (1–2 h) at each of the facilities. We could find no other studies that proposed methods to predict instances of understaffing; however, in two papers Hoot et al. describe the utility of various ED crowding/work indices compared to logistic regression and neural network models based on various operational inputs for predicting periods of ambulance diversion [37,38]. Again, we would have liked to have chosen an operational outcome for which predictive models had already been developed; however, we found their choice of ambulance diversion problematic for three reasons. First, ambulance diversion is an extremely rare occurrence at our sites. Second, the decision to go on diversion is often a very subjective one, and third we believed that more granular forecasts of the demand for key resources such as beds, laboratory, and radiology services would likely be more informative and would give ED clinicians and administrators better insight into how to manage and even avert severe overcrowding [68–70]. Despite a different outcome of interest, the results of Hoot's studies provide some context for how well our multivariate forecasting models performed in predicting a certain operational state (understaffing) in the ED. Hoot reports that the AROC for predicting ambulance diversion at 1 h ahead for a recurrent neural network model based on 14 operational variables was 0.957 [37]. He also reports that the 1 h ahead AROCs for several other classifiers ranged from 0.81 to 0.954 [37,38]. At 1 h ahead, our multivariate forecasting models were able to predict ED census within an average absolute error of approximately two patients, and showed good ability to predict extreme departures from normal ED census levels. Using the forecasted deviation of ED census from expected levels as the sole input to a logistic regression model provided comparable discriminatory power (0.85–0.91) to that which was achieved in using a variety of other indicators to predict ambulance diversion.

Emergency medicine is complex and depends on the clinical skills of individuals as well as the ability of those individuals to function in a collaborative manner [71]. During a typical ED visit multiple physicians, nurses, support staff, and technicians interact to care for the patient. The effectiveness of their interactions is largely determined by the social and organizational norms of the ED [71,72]. As noted in our limitations we did not consider these social and organizational factors; however, it is likely that these factors could affect the utility of our models in unexpected ways. Some of the social and organizational factors we believe are likely to affect the utility of forecasting models are budgetary constraints, nursing shortages, specialist shortages, federal, and state regulations, and the availability of comprehensive information systems [71–76].

5. Conclusion

In summary, we found that multivariate VAR models provided insight into the dynamics of demand in the ED and the inpatient hospital at our local sites, and provided more accurate forecasts of ED census for extended forecast horizons when compared to standard univariate time series methods. The VAR models also provided more accurate forecasts of the demands for diagnostic resources. However, despite the improved accuracy we are not confident that these forecasts could be used reliably in the clinical setting. Given pending legislation that is likely to require most US hospitals to comply with nurse staffing ratios we sought to explore the utility of the VAR forecasting models in providing advanced warning of instances where those ratios would be exceeded. We found that the predicted deviations in ED census provided moderate predictive discriminatory power for short forecast horizons. The development of means to accurately forecast census and the demand diagnostic resources in the ED can improve planning and the management of resources in an environment where the allocation of resources is becoming increasingly important. Clinical information systems are critically important both as a source of real-time and historical data from which models can be developed and as a platform upon which decision support can be delivered to clinicians and administrators as they are faced challenging operational decisions. Along with the methods proposed in this paper, we advocate a focus on the development and use of robust analytical methods such as queuing theory, optimization, and simulation modeling that can be used to provide decision support for important tasks such as clinical staffing, real-time monitoring, and forecasting.

Appendix A. Most frequently ordered laboratory batteries by percentage of overall laboratory volumes at three hospital emergency departments

Test name	Percentage of total laboratory volumes (%)
Complete blood count	13.55
Basic metabolic panel	7.53
Urinalysis, microscopic	6.07
Comprehensive metabolic Panel	5.79
Urinalysis, macroscopic	5.31
Creatine kinase—MB	4.37
Lipase	3.64
Troponin I	3.50
Prothrombin time	3.00
Amylase	2.87
Partial thromboplastin Time	2.32
Hematocrit	2.20
Magnesium	2.16
HCG Beta quantitative	1.86
Drug abuse screening	1.73
Hepatic function panel	1.71
Urinalysis, macroscopic	1.71
Drug abuse screening	1.57
Urine culture	1.46
Blood culture	1.29
Human chronic Gonadotropin	1.25
Lactic acid, plasma (venous)	1.12
Troponin II	0.97
Thyrotropin	0.91
D Dimer quantitative	0.89
B-Type natriuretic peptide	0.89
Total	79.64

Appendix B. Regression parameter, *t*-value, and *p*-value estimates for models of ED census, laboratory, radiography, and computed tomography volumes. Lagged values of a given variable are indicated by "variable name, . . ., e.g., "ED Arrivals, 1 indicates the observed ED patient arrivals in the hour prior to the hour for which the forecast is being made

Variable	Model parameters for ED Census			Model parameters for ED laboratory volumes			Model parameters for ED radiography volumes			Model parameters for ED CT volumes		
	Estimate	*t*-Value	*p*-Value	Estimate	*t*-Value	*p*-Value	Estimate	*t*-Value	*p*-Value	Estimate	*t*-Value	*p*-Value
Constant	5.42	8.90	<0.01	6.26	5.08	<0.01	1.76	4.61	<0.01	0.96	3.49	<0.01
Trend	−0.01	-2.15	0.03	0.01	1.26	0.21	0.01	−1.30	0.19	0.01	1.42	0.16
Census, 1	0.71	42.64	<0.01	0.07	1.99	0.05	0.03	2.47	0.01	0.02	2.81	0.01
Census, 2	−0.04	−2.16	0.03	−0.02	−0.23	0.81	−0.01	−1.04	0.30	−0.01	−0.56	0.57
Census, 3	0.05	2.33	0.02	0.02	0.43	0.67	0.01	0.41	0.68	0.01	1.43	0.15
Census, 4	0.01	0.04	0.97	−0.02	−0.39	0.7	0.01	0.71	0.48	0.01	0.68	0.5
Census, 5	0.02	0.95	0.34	0.01	0.09	0.93	0.01	0.51	0.61	−0.01	−1.17	0.24
Census, 6	−0.01	−0.05	0.96	−0.02	−0.23	0.82	0.01	0.75	0.46	0.01	−0.4	0.69
Census, 7	0.02	0.45	0.65	0.05	1.23	0.22	−0.02	−1.43	0.15	0.01	0.94	0.35
Census, 8	−0.02	−0.56	0.57	−0.05	−1.61	0.11	0.01	−0.28	0.78	−0.01	−1.21	0.23
Laboratory, 1	0.05	8.25	<0.01	0.04	0.86	0.39	−0.01	−0.91	0.36	0.01	0.42	0.68
Laboratory, 2	0.01	2.14	0.03	−0.03	−0.56	0.57	0.02	1.04	0.30	0.01	−0.34	0.73
Laboratory, 3	−0.01	−0.78	0.44	−0.03	−0.59	0.55	0.01	−0.07	0.94	0.01	0.67	0.5
Laboratory, 4	−0.02	−1.21	0.23	−0.03	−0.64	0.53	−0.01	−0.49	0.63	0.01	−−0.15	0.88
Laboratory, 5	0.02	1.00	0.32	−0.04	−0.81	0.42	−0.01	−0.35	0.73	0.01	0.25	0.81
Laboratory, 6	−0.01	−1.75	0.08	−0.02	−0.47	0.64	0.01	0.48	0.63	0.01	−0.25	0.81
Laboratory, 7	−0.01	−0.53	0.60	−0.01	−0.21	0.83	0.01	−0.13	0.90	−0.02	−1.88	0.06
Laboratory, 8	−0.01	−1.83	0.07	−0.03	−0.51	0.61	−0.02	−1.02	0.31	0.02	2.09	0.04

Appendix B (*continued*)

Variable	Model parameters for ED Census			Model parameters for ED laboratory volumes			Model parameters for ED radiography volumes			Model parameters for ED CT volumes		
	Estimate	*t*-Value	*p*-Value	Estimate	*t*-Value	*p*-Value	Estimate	*t*-Value	*p*-Value	Estimate	*t*-Value	*p*-Value
Radiography, 1	0.01	0.02	0.98	0.05	3.69	<0.01	0.01	1.56	0.12	0.01	0.02	0.98
Radiography, 2	−0.01	−0.16	0.88	−0.01	−0.8	0.43	0.01	−0.69	0.49	0.01	0.89	0.37
Radiography, 3	0.03	1.69	0.09	−0.01	−0.83	0.41	0.01	0.70	0.49	0.01	−0.03	0.97
Radiography, 4	−0.03	−1.61	0.11	−0.02	−0.86	0.39	−0.01	−0.97	0.33	0.01	−0.47	0.64
Radiography, 5	−0.03	−1.54	0.12	0.01	0.59	0.56	0.01	−0.21	0.83	0.01	0.42	0.67
Radiography, 6	0.01	0.23	0.82	−0.02	−1.23	0.22	−0.01	−0.91	0.36	0.01	−0.98	0.33
Radiography, 7	−0.03	−1.52	0.13	0.02	0.38	0.7	0.01	1.56	0.12	0.01	−0.92	0.36
Radiography, 8	0.01	0.60	0.55	0.02	0.58	0.56	0.01	−1.04	0.30	0.01	1.34	0.18
Computed tomography, 1	0.08	3.09	<0.01	−0.06	−1.64	0.1	−0.03	−2.75	0.01	−0.01	−1.61	0.11
Computed tomography, 2	0.02	0.20	0.84	−0.02	−0.13	0.9	0.01	0.37	0.71	0.01	0.66	0.51
Computed tomography, 3	0.03	1.27	0.20	−0.07	−1.79	0.07	0.01	0.36	0.72	−0.01	−1.11	0.27
Computed tomography, 4	0.01	0.16	0.87	−0.02	−0.61	0.54	0.03	2.11	0.04	−0.01	−0.73	0.47
Computed tomography, 5	−0.05	−2.15	0.03	−0.03	−0.73	0.46	−0.03	−2.39	0.02	0.01	0.32	0.75
Computed tomography, 6	−0.02	−0.26	0.80	0.05	1.24	0.22	0.01	0.39	0.70	0.01	0.87	0.39
Computed tomography, 7	−0.03	−1.19	0.24	−0.07	−1.67	0.09	0.03	2.85	<0.01	0.01	1.57	0.12
Computed tomography, 8	0.01	0.09	0.93	0.08	2.11	0.03	0.01	−0.32	0.75	−0.01	−1.12	0.26
Inpatient census, 1	0.01	2.01	0.04	−0.01	−0.45	0.65	0.01	2.01	0.04	0.01	0.33	0.74
Inpatient census, 2	−0.02	−0.88	0.38	0.02	0.98	0.32	0.01	−0.31	0.76	0.01	−0.04	0.97
Inpatient census, 3	−0.01	−1.24	0.22	−0.02	−0.88	0.38	0.01	0.50	0.62	0.01	−0.17	0.87
Inpatient census, 4	0.01	0.31	0.76	0.02	0.82	0.41	0.01	1.20	0.23	0.01	−1.08	0.28
Inpatient census, 5	−0.02	−0.86	0.39	0.02	2.22	0.03	0.01	−0.34	0.73	0.01	0.41	0.68
Inpatient census, 6	0.02	0.66	0.51	0.02	0.66	0.51	0.01	−0.02	0.98	0.01	0.74	0.46
Inpatient census, 7	−0.02	−0.65	0.52	0.02	2.19	0.03	0.01	−1.15	0.25	0.01	0.02	0.98
Inpatient census, 8	0.02	0.99	0.32	0.02	0.94	0.35	0.01	−0.10	0.92	0.01	−0.04	0.97
Inpatient laboratory, 1	0.01	0.07	0.94	0.02	1.11	0.27	0.01	0.20	0.84	0.01	2.02	0.04
Inpatient laboratory, 2	−0.01	−0.55	0.58	−0.02	−0.34	0.74	0.01	0.04	0.97	0.01	−0.01	0.99
Inpatient laboratory, 3	0.01	0.97	0.33	−0.01	−0.13	0.9	−0.01	−1.77	0.08	0.01	−0.3	0.76
Inpatient laboratory, 4	0.01	0.46	0.64	0.01	0.59	0.55	0.01	1.21	0.23	0.01	−0.23	0.82
Inpatient laboratory, 5	0.01	1.25	0.21	−0.02	−1.02	0.31	0.01	1.18	0.24	0.01	−0.5	0.62
Inpatient laboratory, 6	−0.01	−0.08	0.94	−0.02	−0.67	0.5	−0.01	−1.28	0.20	−0.01	−1.69	0.09
Inpatient laboratory, 7	−0.01	−0.24	0.81	−0.01	−0.45	0.65	0.01	−0.15	0.88	0.01	2.42	0.02
Inpatient laboratory, 8	0.01	1.05	0.29	0.02	0.41	0.68	0.01	0.49	0.63	0.01	−0.83	0.41
Inpatient radiography, 1	0.02	1.45	0.15	−0.01	−1.17	0.24	0.01	−1.26	0.21	0.02	5.8	<0.01
Inpatient radiography, 2	−0.02	−0.45	0.65	0.02	0.49	0.63	0.01	−1.30	0.19	0.01	3.7	<0.01
Inpatient radiography, 3	0.02	0.69	0.49	0.03	2.31	0.02	0.01	0.53	0.60	0.01	0.43	0.67
Inpatient radiography, 4	0.01	0.04	0.97	0.03	2.21	0.03	−0.01	−1.63	0.10	0.01	1.14	0.25
Inpatient radiography, 5	0.02	0.76	0.45	0.05	4.33	<0.01	0.01	−0.17	0.87	0.01	0.07	0.94
Inpatient radiography, 6	−0.01	−1.01	0.31	0.02	0.66	0.51	0.01	−1.19	0.23	0.01	−0.44	0.66
Inpatient radiography, 7	−0.01	−0.40	0.69	0.02	0.51	0.61	0.01	0.03	0.97	0.01	0.4	0.69
Inpatient radiography, 8	0.02	1.86	0.06	0.02	0.59	0.55	0.01	0.76	0.45	0.01	0.73	0.47
Inpatient computed tomography, 1	−0.03	−1.40	0.16	−0.13	−3.41	<0.01	−0.04	−3.79	<0.01	−0.01	−0.66	0.51
Inpatient computed tomography, 2	0.02	0.78	0.43	−0.03	−0.78	0.44	0.02	1.78	0.07	0.01	1.02	0.31
Inpatient computed tomography, 3	0.02	0.50	0.62	−0.01	−0.32	0.75	0.02	1.53	0.13	0.01	1.54	0.12
Inpatient computed tomography, 4	0.01	0.77	0.44	−0.01	−0.04	0.97	0.01	0.52	0.60	0.01	−0.13	0.9
Inpatient computed tomography, 5	−0.01	−0.14	0.89	−0.03	−0.87	0.39	0.01	−0.23	0.82	0.02	2.01	0.04
Inpatient computed tomography, 6	0.04	2.18	0.03	0.04	1.02	0.31	−0.01	−0.92	0.36	0.02	2.49	0.01
Inpatient computed tomography, 7	−0.04	−1.86	0.06	0.06	1.58	0.11	0.01	1.04	0.30	−0.01	−0.93	0.35
Inpatient computed tomography, 8	0.07	3.50	<0.01	−0.02	−0.58	0.56	0.01	−0.16	0.88	0.01	−0.39	0.7

(*continued on next page*)

Appendix B (*continued*)

Variable	Model parameters for ED Census			Model parameters for ED laboratory volumes			Model parameters for ED radiography volumes			Model parameters for ED CT volumes		
	Estimate	*t*-Value	*p*-Value	Estimate	*t*-Value	*p*-Value	Estimate	*t*-Value	*p*-Value	Estimate	*t*-Value	*p*-Value
Monday	0.25	1.47	0.14	0.99	1.38	0.17	−0.19	−0.83	0.40	0.09	0.57	0.57
Tuesday	−0.30	−1.71	0.09	−0.83	−1.13	0.26	−0.54	−2.35	0.02	0.2	1.21	0.23
Wednesday	0.19	1.03	0.30	−1.63	−2.13	0.03	−0.56	−2.37	0.02	0.18	1.04	0.3
Thursday	0.04	0.21	0.84	−2.27	−2.87	<0.01	−0.76	−3.13	<0.01	0.05	0.28	0.78
Friday	−0.19	−1.01	0.31	−1.99	−2.44	0.01	−0.86	−3.41	<0.01	0.05	0.28	0.78
Saturday	0.18	1.13	0.26	−2.31	−2.69	0.01	−1.13	−4.25	<0.01	−0.11	−0.58	0.56
1:00 AM	−0.51	−1.44	0.15	−1.21	−1.09	0.28	−1.11	−3.23	<0.01	−0.38	−1.54	0.12
2:00 AM	3.84	6.84	<0.01	−0.85	−0.77	0.44	−0.74	−2.15	0.03	0.05	0.2	0.84
3:00 AM	−0.37	−0.97	0.33	1.22	1.08	0.28	−0.32	−0.92	0.36	0.06	0.23	0.82
4:00 AM	0.40	1.02	0.31	1.92	1.69	0.09	−0.17	−0.48	0.63	0.24	0.95	0.34
5:00 AM	−0.20	−0.50	0.62	1.07	0.95	0.34	0.24	0.69	0.49	−0.07	−0.28	0.78
6:00 AM	0.11	0.26	0.79	4.81	4.26	<0.01	0.97	2.78	0.01	0.23	0.92	0.36
7:00 AM	0.45	0.82	0.41	1.89	1.69	0.09	1.07	3.09	<0.01	0.29	1.15	0.25
8:00 AM	1.78	3.25	<0.01	2.06	1.86	0.06	0.68	2.00	0.05	0.36	1.45	0.15
9:00 AM	2.64	4.76	<0.01	2.49	2.88	<0.01	0.55	2.07	0.04	0.27	1.39	0.17
10:00 AM	4.17	7.46	<0.01	2.94	3.55	<0.01	0.45	1.74	0.08	0.36	1.98	0.05
11:00 AM	5.47	9.83	<0.01	3.79	4.91	<0.01	0.69	2.88	<0.01	0.29	1.7	0.09
12:00 PM	5.19	9.39	<0.01	2.76	3.85	<0.01	0.93	4.21	<0.01	0.33	2.05	0.04
1:00 PM	4.41	8.05	<0.01	3.6	5.41	<0.01	1.08	5.23	<0.01	0.5	3.35	<0.01
2:00 PM	4.70	11.03	<0.01	3.1	4.85	<0.01	0.90	4.54	<0.01	0.31	2.16	0.03
3:00 PM	4.01	9.80	<0.01	3.54	5.72	<0.01	0.84	4.39	<0.01	0.66	4.81	<0.01
4:00 PM	3.70	9.69	<0.01	2.95	5.06	<0.01	0.81	4.48	<0.01	0.34	2.62	0.01
5:00 PM	3.27	9.23	<0.01	1.96	3.62	<0.01	0.61	3.67	<0.01	0.21	1.73	0.08
6:00 PM	3.71	11.29	<0.01	0.67	14.78	<0.01	0.17	12.02	<0.01	0.05	5.1	<0.01
7:00 PM	−0.92	−2.51	0.01	0.15	3.35	<0.01	0.03	2.41	0.02	−0.01	−0.68	0.49
8:00 PM	3.70	11.73	<0.01	0.03	0.62	0.54	0.01	0.20	0.84	−0.02	−2	0.05
9:00 PM	3.12	10.21	<0.01	0.05	0.98	0.33	0.03	2.32	0.02	−0.02	−1.63	0.1
10:00 PM	3.24	11.24	<0.01	−0.01	−0.29	0.78	−0.03	−2.04	0.04	−0.01	−0.54	0.59
11:00 PM	2.51	9.40	<0.01	−0.02	−0.53	0.59	−0.02	−1.45	0.15	−0.01	−0.98	0.33
ED arrivals, 1	0.11	4.96	<0.01	−0.03	−0.21	0.83	0.01	0.39	0.70	−0.03	−0.95	0.34
ED arrivals, 2	0.02	0.82	0.41	−0.01	−0.09	0.93	0.05	1.31	0.19	−0.05	−1.73	0.08
ED arrivals, 3	−0.05	−2.00	0.05	−0.03	−0.1	0.92	−0.03	−0.24	0.81	0.06	0.73	0.47
ED arrivals, 4	−0.02	−0.78	0.44	−0.2	−0.55	0.59	0.04	0.39	0.70	0.06	0.8	0.42
ED arrivals, 5	−0.03	−1.17	0.24	−0.5	−1.32	0.19	−0.06	−0.53	0.60	0.13	1.55	0.12
ED arrivals, 6	−0.01	−0.60	0.55	−0.57	−1.42	0.16	0.12	0.95	0.34	0.06	0.63	0.53
ED arrivals, 7	−0.01	−0.13	0.90	−1.04	−2.66	0.01	−0.08	−0.65	0.52	0.04	0.44	0.66
ED arrivals, 8	0.02	1.16	0.25	−0.08	−0.24	0.81	0.22	2.21	0.03	0.1	1.44	0.15

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