Root Cause Analysis of Emergency Department Crowding and Ambulance Diversion in Massachusetts

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Emergency Room Diversion Study: Analysis and Findings

Phase I

Phase I of these investigations involved formulation of a conceptual model that would permit data collection and analysis germane to the problem of ambulance diversion. As preparation for this study, a wide range of relevant medical publications, policy statements and commissioned studies were reviewed. This was followed by personal interviews with representatives in government, hospital administration, public health and the Emergency Medicine community. Information was gathered from throughout Massachusetts and from other key states. Particular attention was given to experience in areas where crowding is particularly severe including metropolitan Boston, San Francisco, Los Angeles and the states of Arizona and Florida. Overall, numerous potential root causes of diversion had been articulated both in the medical literature and lay press, but empirical data to support them were lacking. Available research tended to be descriptive, documenting the extent of crowding without clear delineation of its sources. Various solutions had been proposed and implemented, all without consistent benefit. A partial summary of this analysis has been previously released by the Massachusetts Health Policy Forum of Brandeis University.

An operations management perspective suggested straightforward input-throughput-output analysis. Hospital utilization data provided by the Division of Health Care Finance and Policy was therefore reviewed alongside diversion data provided by regional EMS providers. Analysis of this information revealed the likely operation of mechanisms both internal and external to emergency departments. In addition to simple supply/demand imbalances for emergency care, diversion and utilization patterns suggested bottlenecks and backlogs related to the competition of emergency and non-emergency patients for similar resources. The interrelationships of hospital services then became the focus of attention and patient care pathways were explored with administrators from the two study hospitals.

Two paradigms for the quantitative study of interrelationships among hospital departments were considered. The first involved an analytical approach wherein each relationship was identified, its stochastic character estimated, and appropriate mathematical models applied. The second involved a simulation approach, wherein stochastic relationships were embedded into computer software that translated real patient flow inputs into utilization and capacity information. Computer simulation was ultimately selected as the route of choice because of its scalability and adaptability.

Phase II

Data Collection/Analysis Effort:

The study was performed at two hospitals in Massachusetts: Hospital A, a large tertiary academic hospital, and Hospital B, a medium-sized acute care community hospital. The following data were collected:

- 42 days of information covering:
- 6000+ admissions
- 8000+ ED visits
- 2000+ staffing/capacity data points
- 300,000+ patient movement/status data points

In order to analyze the relationship between diversion status and other factors within the hospital environment all measures were split into observations at one hour increments. The study period of 42 days, with 24 hours per day, yielded a total of 1008 full sets of observations. The analysis required collection of patient flow data well beyond the usual capabilities of contemporary hospital information systems.

Point-biserial coefficients of correlation, with diversion status as the binary variable, were examined against a variety of factors. Comparisons when using full hours of diversion versus partial hours as the “true” condition did not reveal significant differences, so partial diversion hours were evaluated as the “true” binary throughout the analysis for the sake of consistency.

It is important to note that in the real world the decisions to commence or cease diversion status are, but their nature, highly subjective. Because the purpose of the study was to examine the root causes of diversion, we did not approach the task from the standpoint of critiquing or attempting to influence this inherent operational subjectivity. As a result, any such analysis is itself subjective to a certain degree.

Because both hospitals straddled EMS regional borders and diversion rules vary by region, each hospital’s data was used for the sake of determining diversion status rather than using centralized EMS data. Also, all diversions were considered equally rather than separately analyzing the factors related to each individual diversion type.

Patterns of diversion were also examined as averages across the hours of the day and the days of the week in order to ascertain relevant hour of the day and day of the week patterns. This data analysis was performed separately for each of the hospitals.

Hospital A:

Diversion Pattern "Hospital A - Diversion Minutes by Hour"

- There were a total of 22 episodes of diversion which started and ended within the study, with an average length of 814 minutes. There was one episode that began prior to the study and ended after the study began and so is not included in this calculation, nor in any calculations which involve the beginning of diversion episodes.
- The hourly diversion pattern shows diversion is highest in the evening hours, settles back down during the early morning hours, and then stays steady until the mid to late afternoon (see Fig. 1).
- The goal of the project was to determine the drivers which create this pattern.

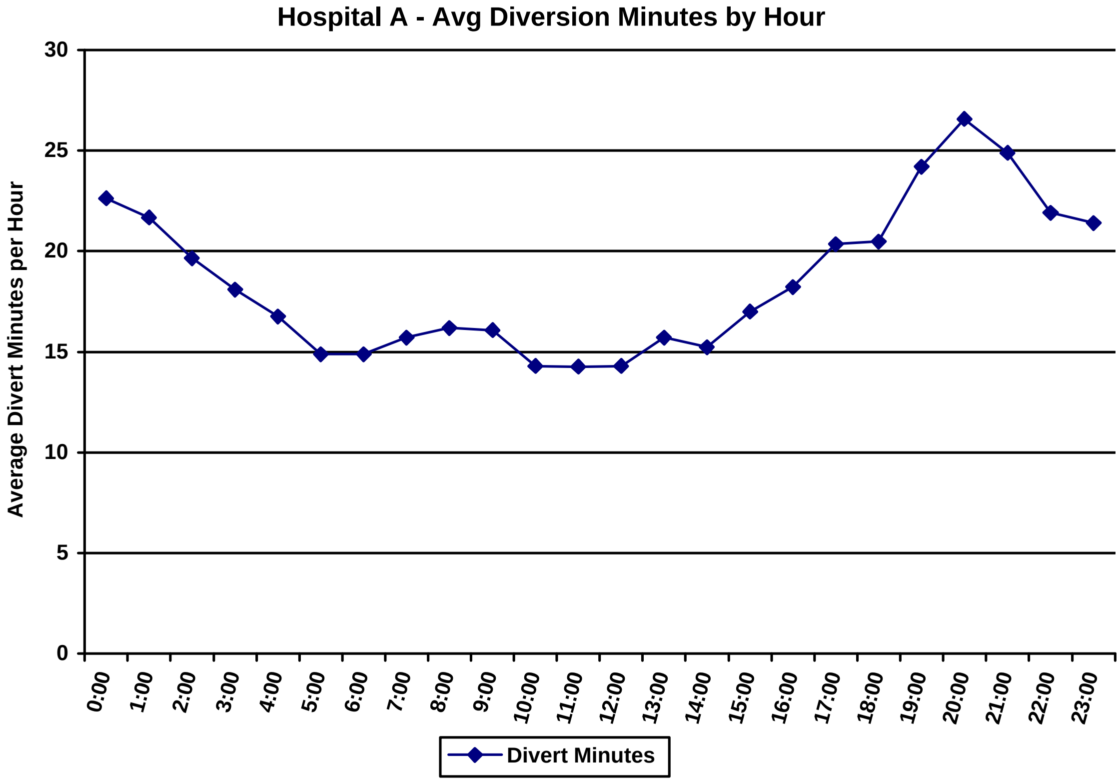

Fig. 1

The following 3 hypotheses were tested to determine the drivers of diversions:

1. ED arrival rate is too high, leading to diversion when the ED becomes full.
2. ED processing of patients is too slow, causing backups that lead to diversion
3. ED arrival and processing rates are fine, but there are not enough beds in the hospital to accommodate the admissions.

Hypothesis #1: ED arrival rate is too high, creating diversion as the ED becomes full.

Test: Correlate # of ED Arrivals with Diversion Status.

Results:

Under this test the number of arrivals to the ED are both a cause and effect. As expected, a direct comparison of ED arrivals to binary ED diversion status (as described above) reveals a slightly negative point-biserial coefficient of correlation (r = -0.141), indicating that ED diversion status is indeed an effective mechanism to reduce arrivals to the ED.

The goal of the test, however, is to determine if the arrivals *lead* to diversion. Therefore, we analyzed only the correlation of non-diversion hours (n = 654 hours) and the hours immediately prior to diversion (n = 22 hours) compared to the arrival rate of patients to the ED during those same hours.

The point-biserial coefficient showed an extremely small relationship between arrivals to the ED in the hour prior to diversion vs. other hours without diversion (1 hour prior r = 0.076). Examination of cumulative arrivals to the ED in the hours prior to diversion exhibit correlations which, although slighter stronger, are still weak (2 hours cumulative r = 0.109 and 3 hours cumulative r = 0.135). It was not possible to create valid cumulative statistics for lags of greater than three hours because there were one or more diversion episodes which occurred with gaps between them of only three full hours.

By comparing the average arrival rate to the ED during the hour prior to diversion (n = 22) versus all other non-diversion hours (n = 654) we can directly examine the possibility that these hours are significantly different from one another. The average hour prior to diversion had an arrival rate of 4.14 patients per hour while the rate for an average non-diversion hour was 3.19 per hour. This difference, however, is explained in part by a time of day bias introduced by the different overall arrival rates by hour of the day. For instance, the average time that diversion begins is in the afternoon hours, a time of the day which exhibits increased average arrival rates to the ED regardless of diversion status. This implies that while overwhelming arrivals to the ED may contribute to ED diversion from time to time, this is not the case in the typical case of diversion. This finding also indicates that hour of the day patterns *are* a contributing factor to ED diversion, although the correlations above indicate that the relationship is less substantial than those in hypothesis #3 below.

By averaging each of the 1008 hourly points from the 42 days by hour of the day, the averages can be arranged in order to see the average daily pattern of diversions (see Fig. 1). By doing the same for ED arrival patterns, we are able to consider the influence of hour of the day patterns of arrival on diversion.

There are seven sets of data (see Fig. 2), each representing a different view of arrivals into the ED. The "Arrivals_0" category only includes new arrivals from the hour in question. Each subsequent category, from "Arrivals_1" to "Arrivals_6" includes one more hour's worth added to the total. In other words, "Arrivals_1" includes arrivals from the current hour added to the arrivals from the previous hour, "Arrivals_2" includes all of "Arrivals_1" plus the arrivals from two hours ago, and so on. This is what accounts for the stacked shape as each additional hour is layered on top. Because average length of stay was 340 minutes, 6 hours is used as the maximum lag. Correlation coefficients from each of these cumulatives to Avg Diversion Minutes by hour are as follows:

Arrivals_0 = -0.073
Arrivals_1 = 0.001
Arrivals_2 = 0.078
Arrivals_3 = 0.165
Arrivals_4 = 0.259
Arrivals_5 = 0.359
Arrivals_6 = 0.460

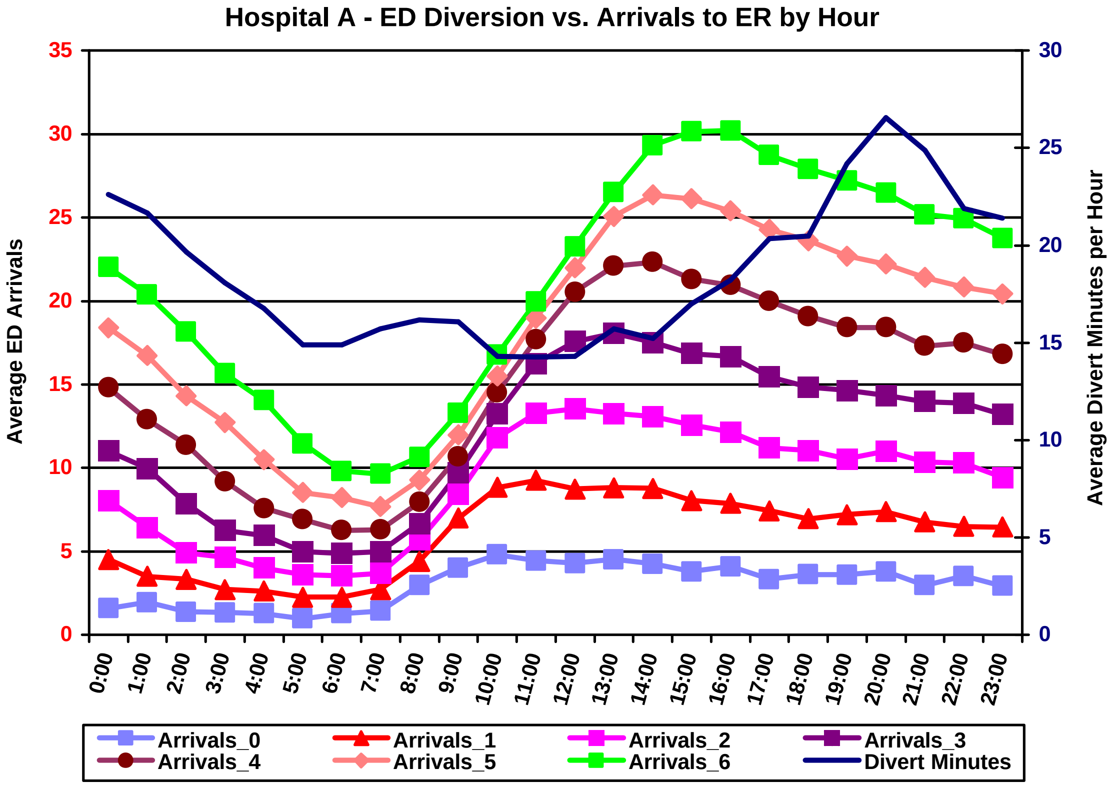

Fig. 2

There is also a possible corollary to hypothesis #1, that overall ED census is a driver of diversion. When counting the non-boarding census and comparing it to diversion status, however, the resulting point-biserial coefficient (r = -0.051) makes clear that this potential explanation should be rejected as well.

Hypothesis #1 Conclusion:

The hourly average results, along with the single hour point-biserial coefficients and small differentials between average arrival rates prior to diversion when compared to averages from the same hours of the day, indicate that the relationship between ED arrivals and ED diversion status is fairly weak.

Hypothesis #2: ED processing of patients is too slow, causing backups that lead to diversion.

Test #1: Correlate "time into slot" to "time admitting called" (or time left ED, in the case of a patient who was not admitted) vs. Diversion Status.

Test #1 Results:

The total amount of process time that can be attributed to the ED processes is that from the time a patient is placed into an ED bed ("time into slot") to the time a disposition is determined ("time admitting called"). These were used as the best available proxy for the ED process for admitted patients, while “time into slot” to “time left ED” is the equivalent for discharged patients. These two measures take into account the process time of actual patient care and are unaffected by queues in the waiting room to get into the ED or by the subsequent wait between the time the decision is made to admit and eventual availability of the bed. As such, this measure is the best unadulterated view of the ED’s ability to care for patients without regard to external factors (other than those which were outside the purview of the study, such as the availability of diagnostic facilities external to the ED).

When comparing the "time into slot" to "time admitting called" (or time left ED, in the case of a patient who was not admitted) with binary divert status (as described above) there was no correlation of consequence found ($r = -0.007$) to indicate that the actual processing time within the ED was at all related to diversion status.

Examining the average processing time between diversion and non-diversion hours provided a similar view, with the average processing time during diversion hours being 327 minutes and during non-diversion 330 minutes. Thus the rate at which patients were processed during diversion was virtually identical to processing times while off diversion. This argues strongly that the diversion process itself is not related to ED slowdowns, significantly increased patient acuity, or elevated patient complexity.

Test #2: Correlate "time into slot" to "time orders received” (or time left ED, in the case of a patient who was not admitted) vs. Diversion Status.

Test #2 Results:

"Time into slot" to "time orders received” provides an indication of the entire ED process, including the necessary step of writing orders for admission to an inpatient bed. This number provides a more complete representation of the ED process, including an overlap with the admitting process.

The correlation coefficient between diversion status and "time into slot" to "time orders received” (or time left ED, in the case of a patient who was not admitted) indicates a stronger relationship (r = 0.173) than that in test #1. The average time between diversion and non-diversion hours is 499 minutes and 438 minutes respectively.

While it is impossible to definitively ascertain which is cause and which is effect, the results from test #1 and the results of hypotheses #3 below suggest that the difference between diversion and non-diversion for test #2 may be accounted for by a lack of available beds leading to reduced urgency to write orders rather than an overall decrease in the processing effectiveness in the ED.

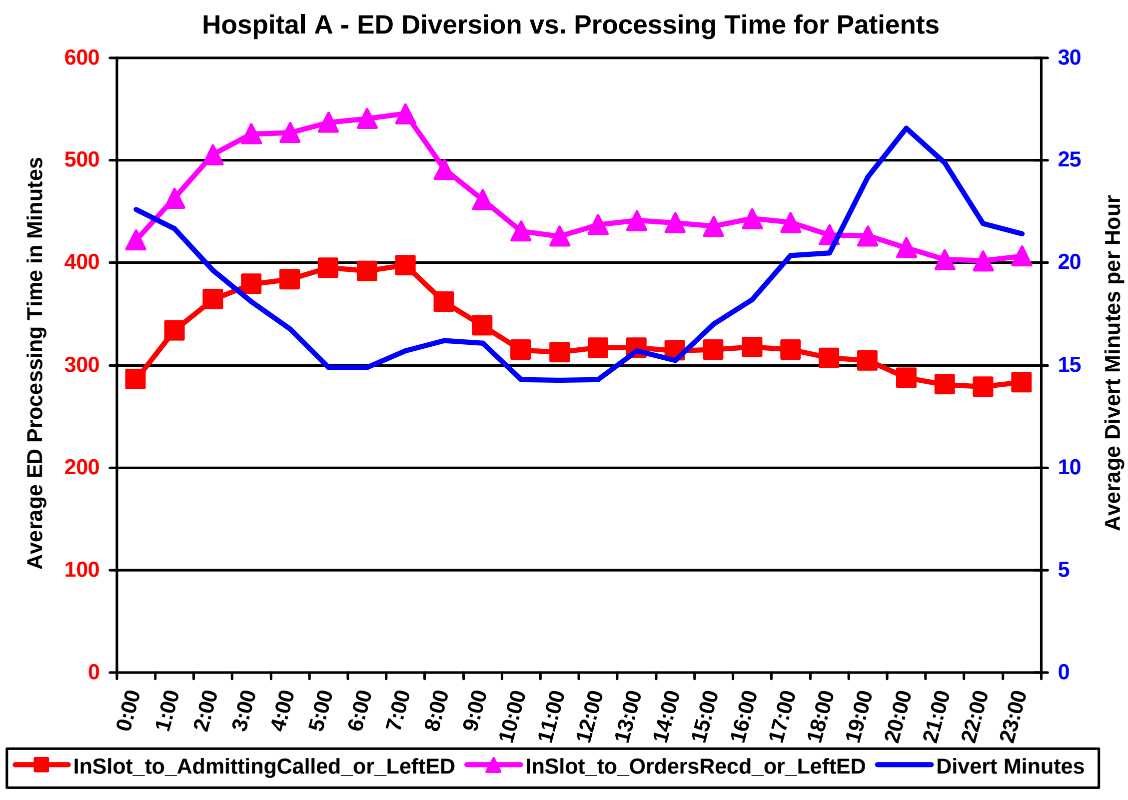

Fig. 3

Hypothesis #2 Conclusion:

Examining processing times versus diversion by hour of the day average also dramatically illustrates that ED diversion is not being driven by processing time differences across hours of the day (see Fig. 3). ED Productivity, as measured here, is actually slightly *improved* during the hours of heaviest diversion in the late evening.

Hypothesis #3: ED arrival and processing rates are fine, but there are not enough beds in the hospital to accommodate the admissions.

Test: Correlate Avg. number of patients waiting for beds (boarding) in the ED vs. Diversion Status.

Results:

Analysis of the relationship between the number of patients waiting for an inpatient room and diversion status reveals a point-biserial coefficient ($r = 0.426$) which is both statistically significant and substantially larger than that observed in the other hypotheses.

We then compared the average number of boarders in the ED during non-diversion hours ($n = 676$ hours) versus diversion hours ($n = 332$ hours). The average non-diversion hour had 4.03 boarding patients present per hour while the rate for the average diversion hour was 7.16 per hour. This signifies that on *average* during diversion there were 78% more patients boarding than during non-diversion hours. Put differently, during diversion hours roughly 1/3 of ED bed capacity was consumed by boarders.

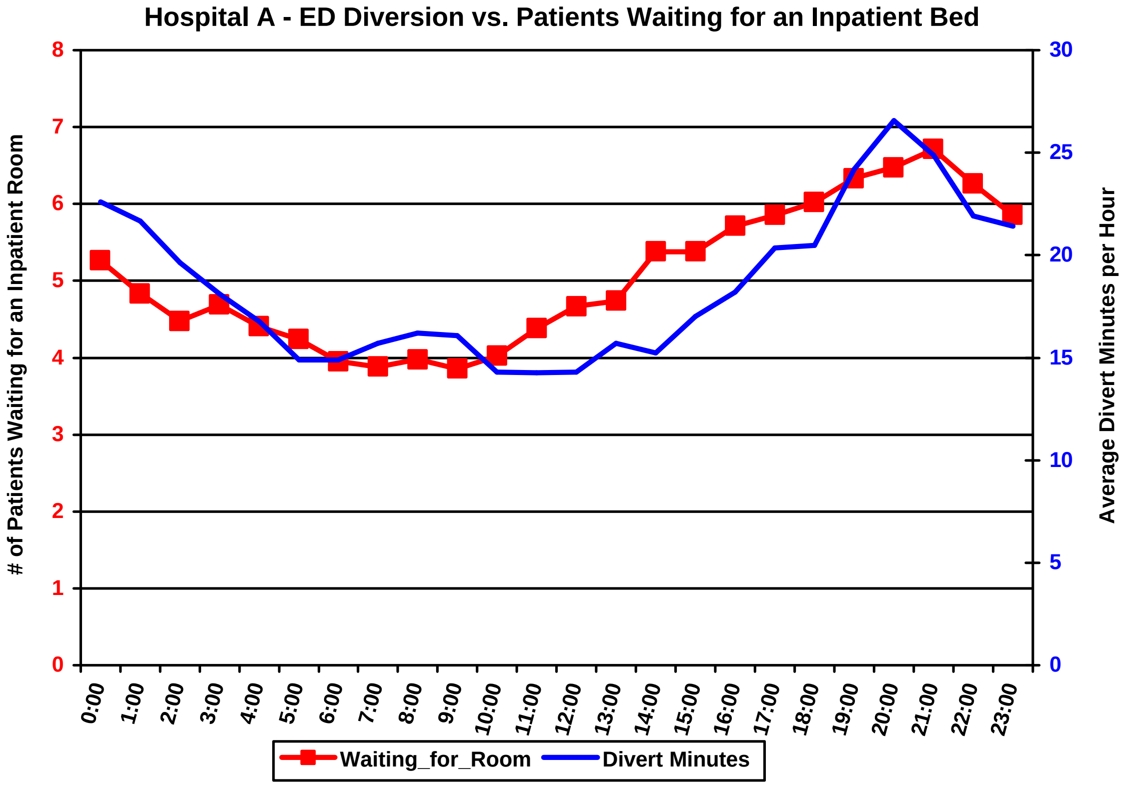

Fig. 4

Further illustration of the relationship between boarders and diversion can be obtained by analyzing the averages by hour of the day in the same fashion as the other hypotheses. The visualization and correlation coefficient speak for themselves, clearly indicating that as the number of patients boarding in the ED increases, so too does diversion (see Fig. 4). Correlation = 0.812

Hypothesis #3 Conclusion:

As discussed under test #2 of hypothesis #2, while it is not possible to conclusively prove causality through statistics alone, it is reasonable to draw conclusions based on rational interpretations of the data in the context of real world knowledge. The correlation between boarders and diversion status, both when examined on a continuous basis and by average across hours of the day, indicate a strong association between lack of inpatient resources and diversion status. Given that hypotheses #1 and #2 have already addressed the input and processing aspects of the process, it is both reasonable and unavoidable to consider boarders as the most significant contributing factor to diversion.

This result argues that the availability of inpatient hospital resources is the primary determinate of diversions.

Census/Admissions/Discharges: Hospital A

Delving into the components of census, attempting to find the "drivers" of boarders in the ED:

"Hospital A - Avg Census, Admissions, Discharges by Hour - All Cases" – Fig. 5

This figure shows pattern of admissions and discharges throughout the day. There is a distinct peak in admissions between 4 PM and 6-7 PM. One can suspect that this peak is a driver of the ED diversions, which peak between 6 PM and 10 PM (see Fig. 1). Surprisingly, average census is actually lowest at 4pm and highest at 10am.

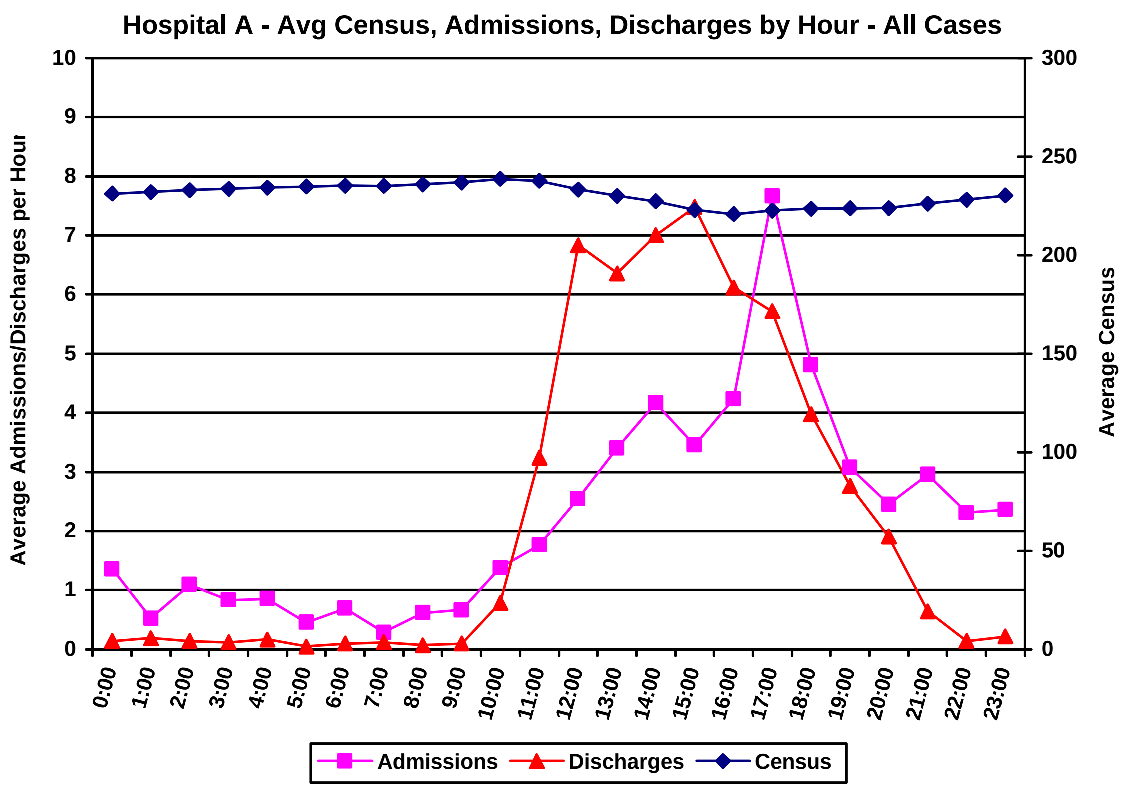

Fig. 5

"Hospital A - Avg Census, Admissions, Discharges by Hour - Scheduled Cases Only"

This figure shows pattern of admissions and discharges for scheduled patients only, demonstrating the influx of patient assignment during the same time as a peak in scheduled admissions (see Fig. 6), and appears to be the cause of the overall peak in admissions.

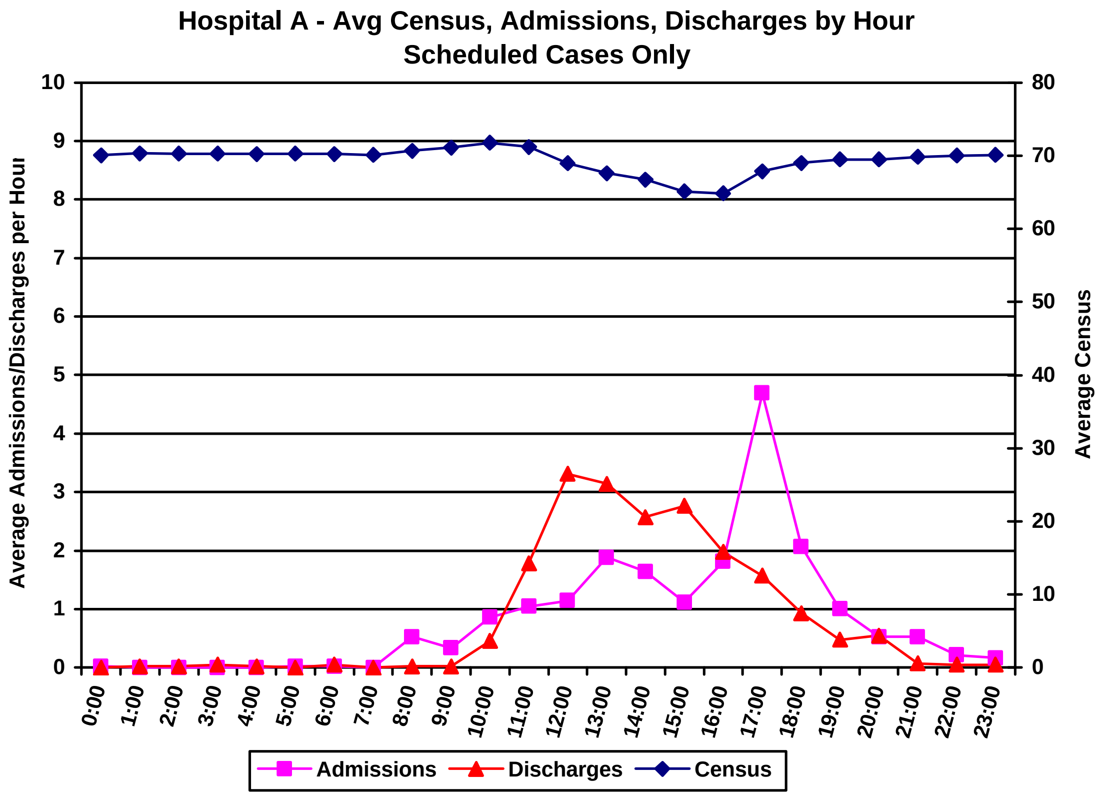

Fig. 6

“Hospital A - Avg Census, Admissions, Discharges by Hour - Unscheduled Cases Only”

This figure shows regularity within the admission pattern of unscheduled patients that is much greater than that for scheduled admissions. It also demonstrates that unscheduled admissions are not likely to cause the peak in overall admissions between 4 PM and 6 PM.

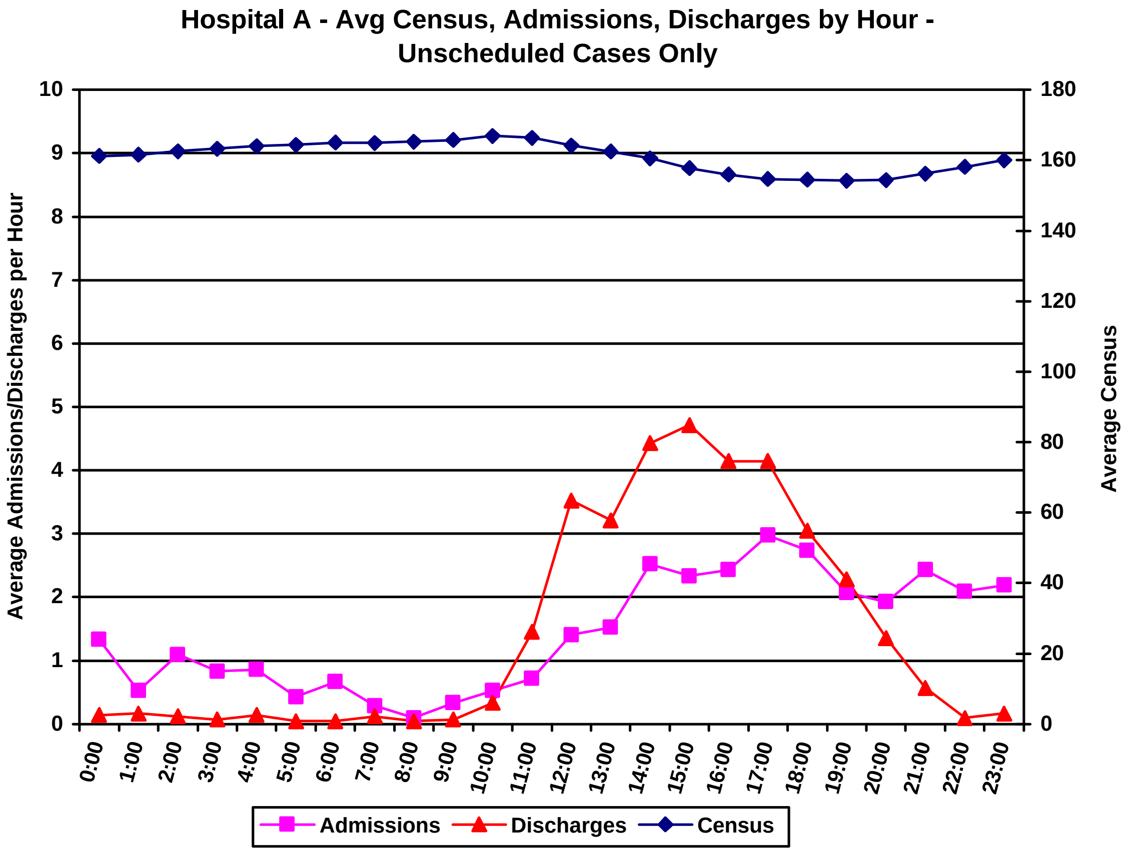

Fig. 7

Diversion and different census ranges:

Figures 1 and 5 demonstrate correlation between hospital admissions and diversions. Can one see a similar correlation between hospital census and diversions? The histogram in Figure 8 demonstrates that such a correlation exists. On this plot the x-axis reflects different ranges of census while the y-axis shows percent of time that the ED is diverting ambulances. The numbers within each census range on the histogram indicate the number of hours during the study period that the census was within that range. For example, when the overall census was between 200 and 209 patients, the ED was diverting ambulances 23% of the time, out of a total of 93 hours during the study when the census was in this range. When census was in the range from 270 to 279 patients the ED was diverting ambulances 100% of time. It is easy to see from this histogram that the greater the census, the greater the percentage of hours when the ED is diverting ambulances. This again demonstrates that an insufficient number of hospital beds is a significant driver of ED diversions.

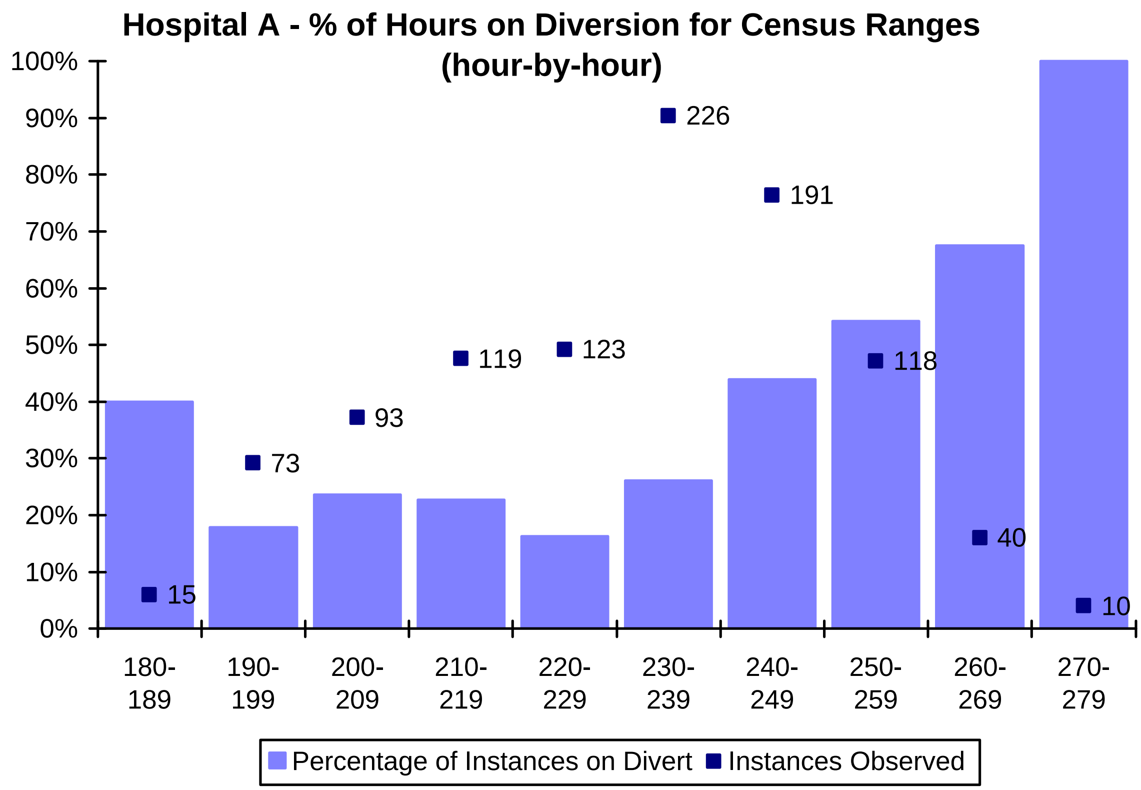

Fig. 8

Examination of Scheduled Admissions

According to Figures 1 and 6, scheduled admissions seem to be a determinant of the ED diversions. The following hypothesis was therefore tested:

Hypothesis: Scheduled Admissions are a significant driver of ED diversion.

Test: Correlate number of Scheduled Admissions (*n* hours prior to divert) with Avg. Minutes of Diversion, by hour.

Results: The results indicate a much closer relationship between scheduled admissions and diversion than between ED arrivals and diversion see Fig. 9). Correlation coefficients from Scheduled Admissions to Avg. Diversion Minutes by hour:

Admissions_0 = -0.017
Admissions_1 = 0.081
Admissions_2 = 0.241
Admissions_3 = 0.405
Admissions_4 = 0.521
Admissions_5 = 0.603
Admissions_6 = 0.686

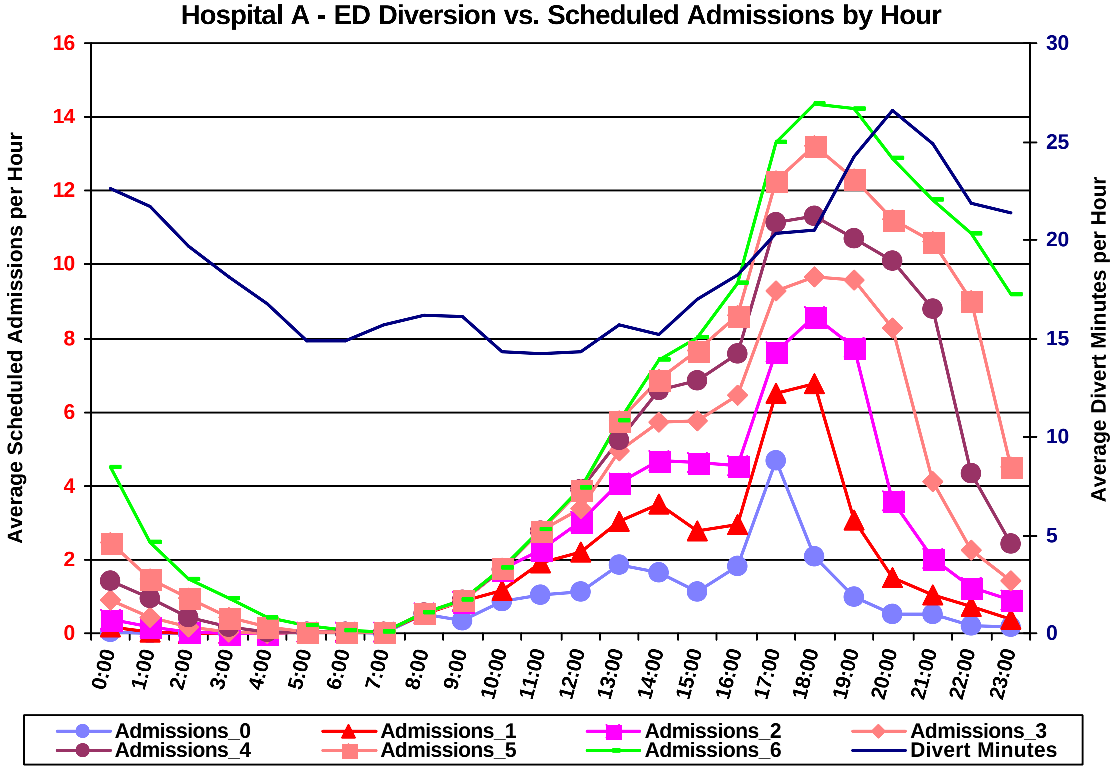

Fig. 9

Scheduled Admissions vs. ED Arrivals

The difference between these two sets of average hour of the day correlation coefficients can best be shown graphically (Fig. 10). The graph shows that for any hour of the day correlation between scheduled admissions and diversion, scheduled admissions correlation is stronger (i.e. higher coefficients) than the correlation between ED arrivals and diversion.

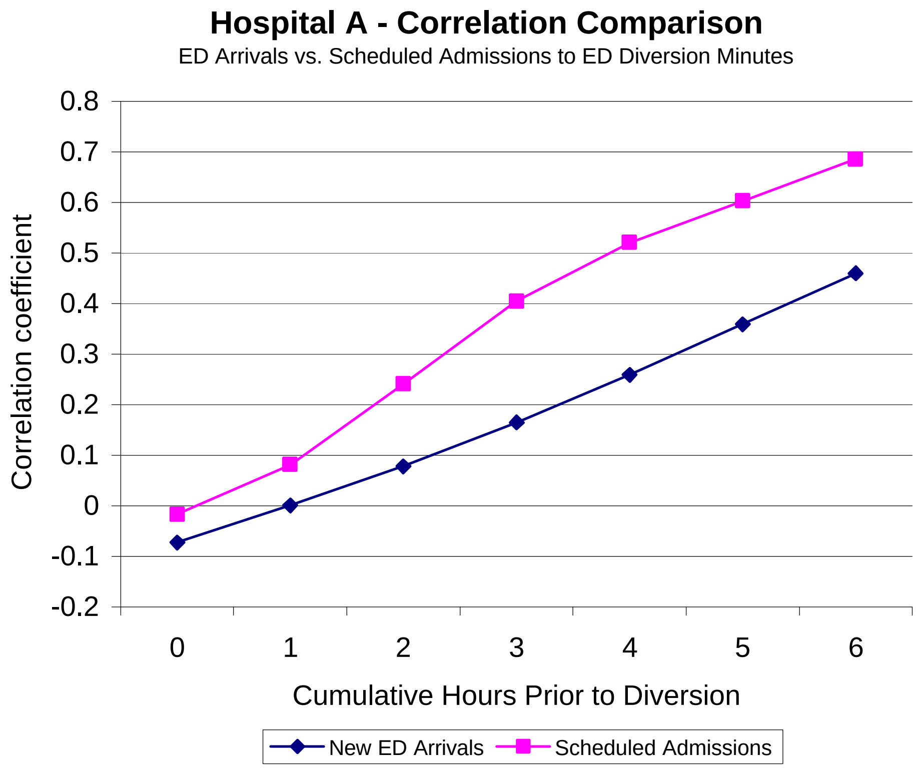

Fig. 10

Analysis of Diversion by Day of Week

The following questions should be answered to analyze the pattern of diversions by the day of the week:

- What are the changes in ED arrivals by day of week?
- What are the changes in scheduled admissions by day of week?
- What are the changes in overall census by day of week?
- Scheduled patients as a % of census by day of week?

ED Diversion vs. ED Arrivals by DOW

Figure 11 shows that ED arrival rates are steady throughout the week, with the exception of Mondays, which exhibit a significant spike. Despite the spike in ED arrivals on Mondays, diversion is lowest (on average) on Mondays. This provides us with another line of evidence that ED diversions are not driven by the pattern of patient arrivals.

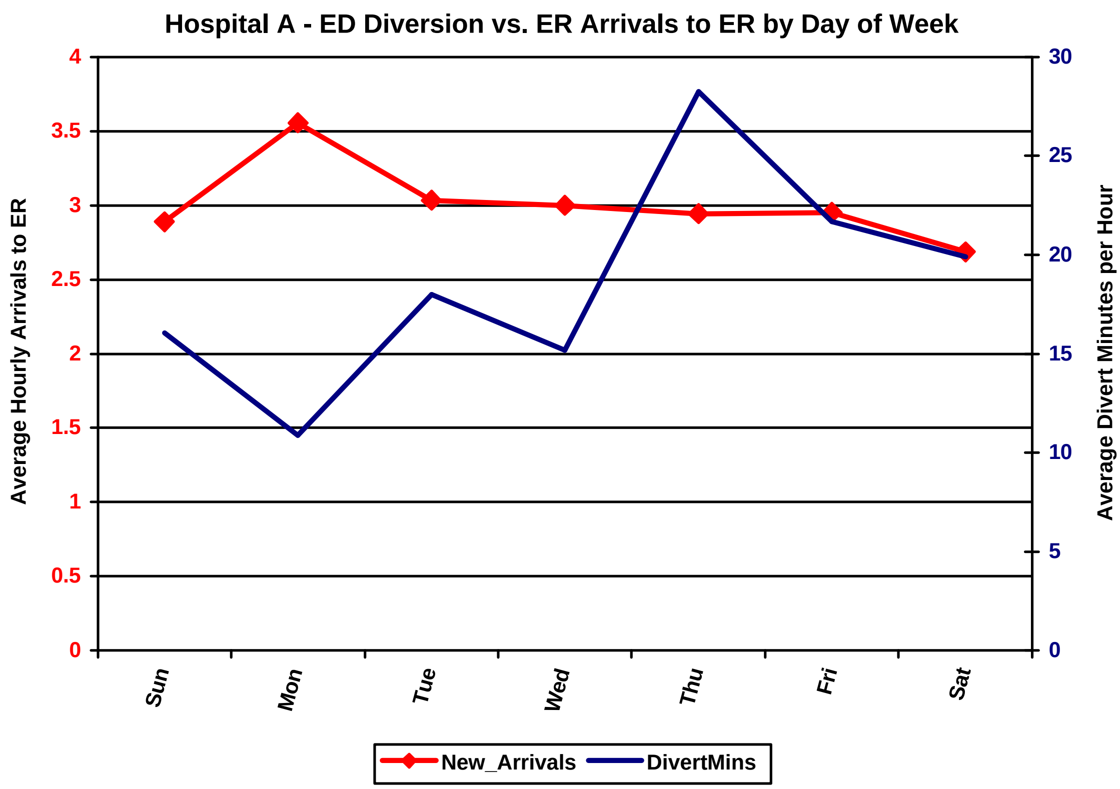

Fig. 11

ED Diversion vs. Scheduled Admissions by DOW

The graph (Fig. 12) clearly shows that ED diversion, at least during weekdays, is highly correlated with scheduled admissions. Peaks in scheduled admissions on Tuesdays and Thursdays correspond with peaks in ED diversion on the same days of the week. However, despite lower scheduled admissions on Thursdays and Fridays than Tuesdays, diversion numbers are still higher on Thursdays and Fridays. This fact suggests that although variability in scheduled admissions is one of the major determinants of ED diversions, it is not the only determinant. To see a more complete pattern, the census variability during the week should be considered.

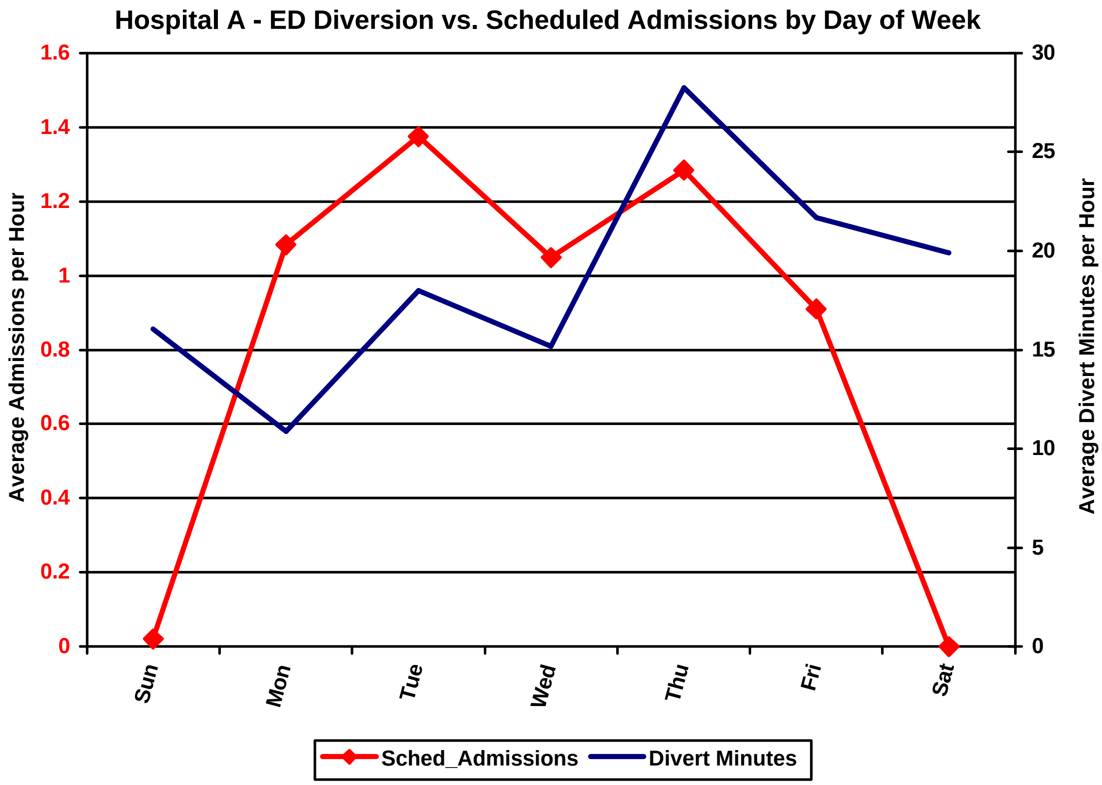

Fig. 12

ED Diversion vs. Census by DOW

Figure 13 demonstrates that as the week moves forward, the census increases, draining out starting on Friday and then falling dramatically over the weekend. This increase in census likely accounts for the increased sensitivity to admissions later in the week, resulting in diversion. In other words, neither high census nor a high level of admissions is necessarily sufficient to cause diversion, but the two in combination make diversion much more likely. Since census is such an powerful driver of diversions it is important to learn what categories of patients constitute census during the week.

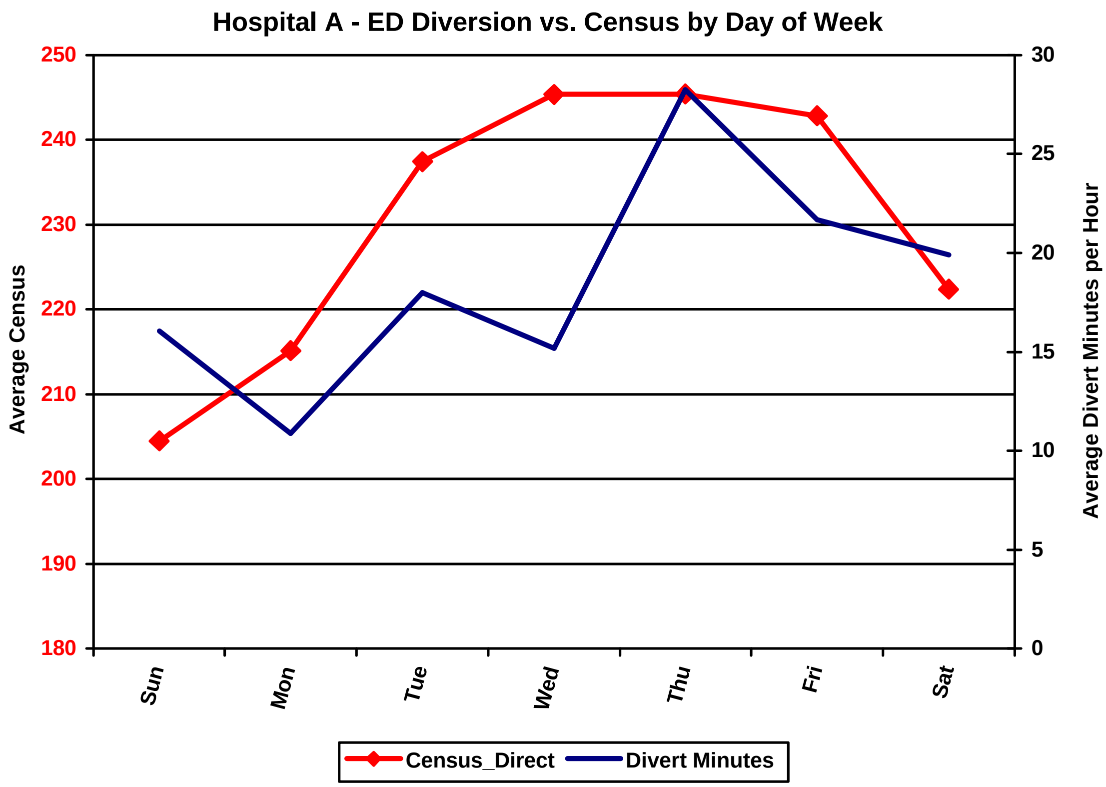

Fig. 13

ED Diversion vs. Scheduled as Percent of Census by DOW

As the week moves forward, scheduled cases make up an increasing percentage of the overall population of the hospital (see Fig. 14). The upward trend in census through the week is due to scheduled patients, not unscheduled patients, whose census peaks on Tuesdays and then slowly declines throughout the remainder of the week. This fact demonstrates that scheduled admissions affect diversions not just through the peaks in admissions during the day (see Fig. 6 and 12), but also through the increased census.

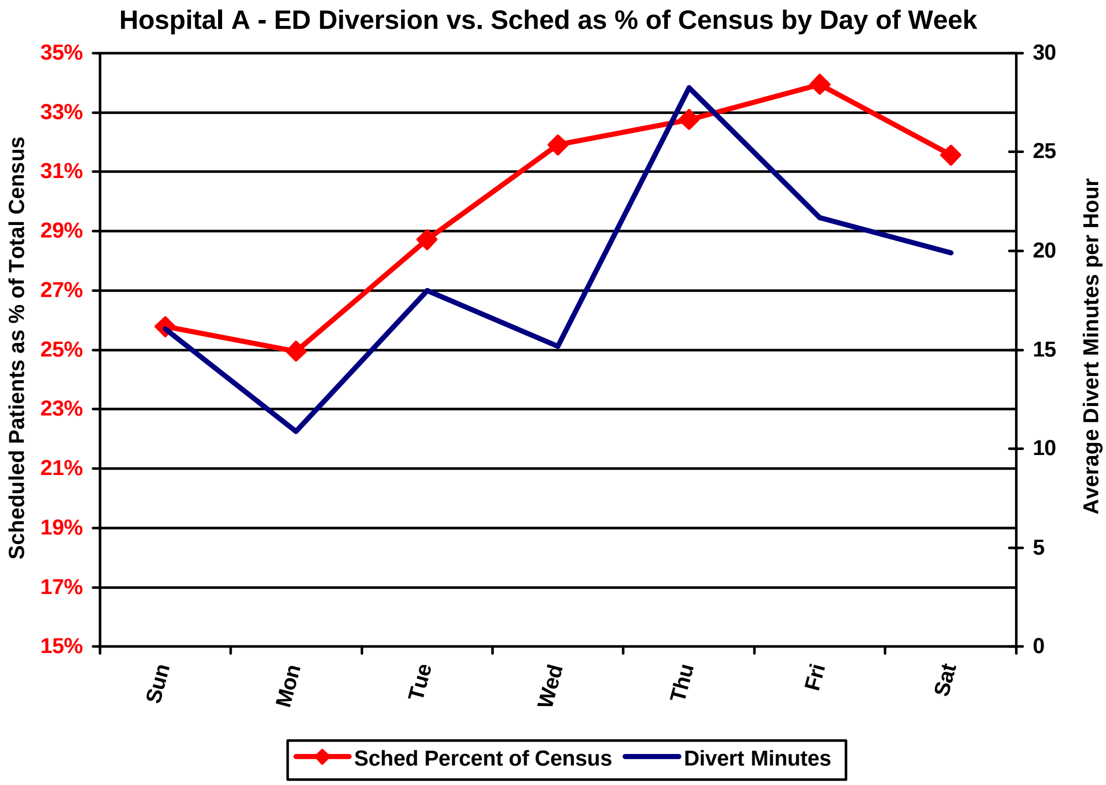

Fig. 14

Hospital A Conclusions:

The patterns exhibited within the data show that ED diversion is not a completely random event and is more often than not driven by forces external to the ED. ED capacity, at least in the instance of this hospital, does not appear to be a significant driver of ED diversion. The pattern of rising scheduled census through the week suggests that opportunities may exist to arrange scheduling in such a fashion that these patient days are more evenly spread out across the week, reducing demand in the latter parts of the week while utilizing more space at the beginning of the week. It should be pointed out, however, that there is a <u>significant diversion problem even during the lowest portions of the week and the lowest portions of the day</u>. These baseline issues cannot be addressed via re-arranging of the schedule, but rather must be tackled from the standpoint of overall hospital capacity. The relative benefit of increasing capacity, compared with re-arranging scheduled cases as well as their combined effect, can only be determined through simulation modeling of the effect of smoothing the schedule.

Hospital B:

Limitations of Data

Due to a change in hospital-wide information systems during the period of study, there were difficulties encountered in a subset of the data collection process. Because some of the ED data was affected, the following conclusions are based on the most reliable data obtained. While overall conclusions are unaffected, specific operational recommendations cannot be made based on this limited study.

Diversion Pattern "Hospital B – Average Divert Percentage by Hour"

- There were 19 episodes of diversion during the course of the study with an average episode length of 475 minutes.
- The hourly diversion pattern shows diversion is highest in the late evening to early morning hours, dropping to zero at noon and then rising rapidly as the afternoon unfolds.
- The project goal was to determine what drivers create this pattern.

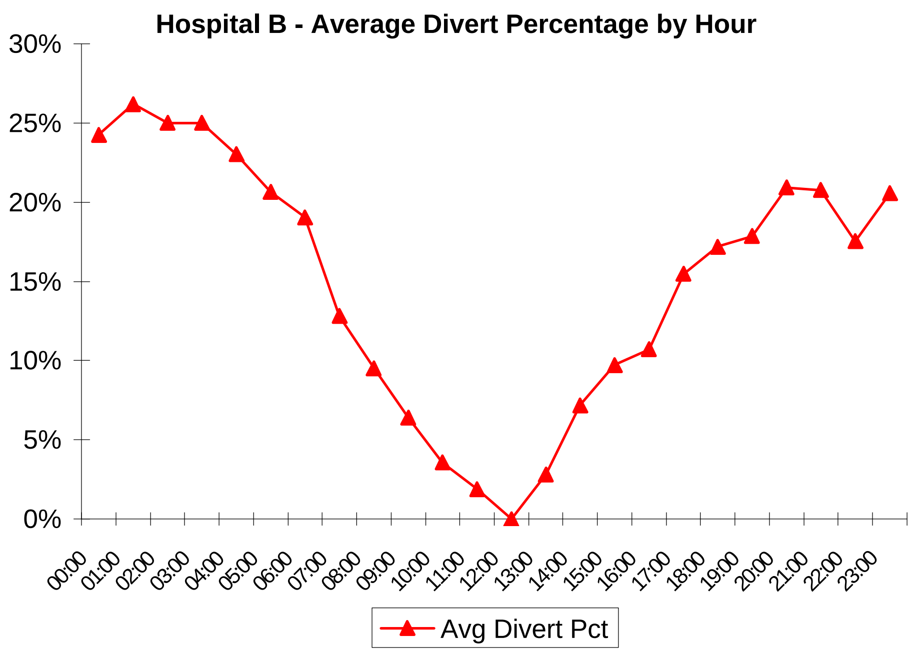

Fig. 15

Again, three hypotheses were analyzed to determine the drivers of diversions:

1. ED arrival rate is too high, leading to diversion when the ED becomes full.
2. ED processing of patients is too slow, causing backups that lead to diversion.
3. ED arrival and processing rates are fine, but there are not enough beds in the hospital to accommodate the admissions.

Hypothesis #1: ED arrival rate is too high, leading to diversion as the ED becomes full.

Test: Correlate # of ED Arrivals with Divert Status.

Results:

As discussed above under Hospital A, because ED arrivals are both cause and effect, we will examine ED arrivals *prior* to diversion, rather than during diversion, in order to determine if arrival rate is a substantial contributing factor to the creation of diversion status.

As above, direct comparison of the ED arrival rate to diversion status via the point-biserial coefficient exhibited an inverse relationship (r = -0.166). When examining the ED arrival rate during hours immediately prior to diversion along with non-diversion hours correlated to binary divert status, similar results to Hospital A were found, with cumulative measures of one hour (r = 0.117), two hours (r = 0.167), and three hours (r = 0.144) each exhibiting positive but weak coefficients of correlation.

As with Hospital A above, the average arrival rates were measured for the hours immediately prior to diversion (n = 19 hours) versus all other non-diversion hours (n = 821 hours). The average arrival rate for the hour prior to diversion was 5.89 patients, while the average for all other non-diversion hours was 3.76 patients per hour. Again, examining the arrival rate during average hour of the start of diversion (5pm) versus this overall average is helpful. The overall arrival rate of 5.43 patients per hour at 5pm suggests that, although periodic spikes in demand may create occasional disruption, hour of the day fluctuations have more of an influence on diversion.

Averaging across the 42 days of data permits examination of the hour of the day fluctuations. There are seven sets of data, each representing a different view of arrivals into the ED (fig. 16). The "Arrivals_0" only includes new arrivals from the hour in question. Each subsequent category, from "Arrivals_1" to "Arrivals_6" includes one more hour's worth added to the total. In other words, "Arrivals_1" includes arrivals from the current hour added to the arrivals from the previous hour, "Arrivals_2" includes all of "Arrivals_1" plus the arrivals from two hours ago, and so on. This accounts for the stacked shape as each additional hour is layered on top. Correlation coefficients to Avg Diversion Minutes are as follows:

Arrivals_0 = -0.728
Arrivals_1 = -0.650
Arrivals_2 = -0.556
Arrivals_3 = -0.446
Arrivals_4 = -0.320
Arrivals_5 = -0.186
Arrivals_6 = -0.049

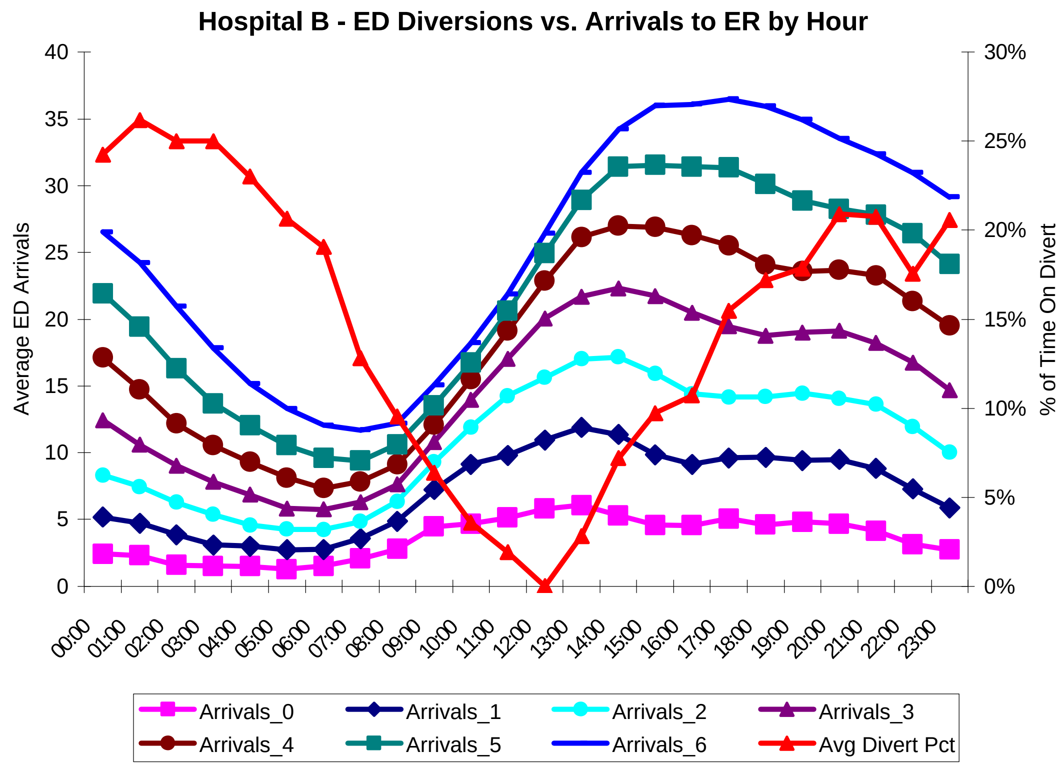

Fig. 16

There is also a possible corollary to hypothesis #1, that overall ED census is a driver of diversion. The point-biserial correlation of non-boarding ED census to divert status (r = 0.000) is nil, a similar result to that seen in Hospital A.

Hypothesis #1 Conclusion:

The lack of a compelling relationship between ED arrivals or ED census to diversion status suggest that while there is interaction between ED arrivals and divert status, the interaction is moderate.

Hypothesis #2: ED processing of patients is too slow, causing backups that lead to diversion.

Test #1: Correlate "time into bed" to "time orders requested" (or time left ED, for patients who were not admitted) vs. Diversion Status.

Test #1 Results:

Explanations of the usage of this measure can be found in the Hospital A section above. The “time orders requested” field is substantially equivalent to the Hospital A “time admitting called” field for the purposes of ascertaining the end of the bulk of the ED process. The point-biserial coefficient from this test (r = -0.133) actually indicates that processing time is *improved* slightly during times of diversion. This is an emphatic rejection of the hypothesis that processing times in the ED are responsible for overcrowding which might lead to diversion.

Consistent results are observed when analyzing the average processing time during diversion hours (289 minutes) and during non-diversion hours (330 minutes), providing a direct indicator of this inverse relationship.

Test #2: Correlate "time into slot" to "time orders complete" (or time left ED, for patients who were not admitted) vs. Diversion Status.

Test #2 Results:

This number provides a more complete representation of the length of the ED process as described in Hospital A above. The point-biserial correlation coefficient (r = 0.126) still indicates that there is not a strong relationship between processing time and diversion, and suggests, when considered in light of the information regarding boarders in hypothesis #3, that the completion of orders may be delayed due to lack of bed availability.

The average results by hour of the day (see Fig. 17) also exhibit a pattern similar to that of Hospital A, indicating that processing time by hour of the day is not a driving factor behind diversion status.

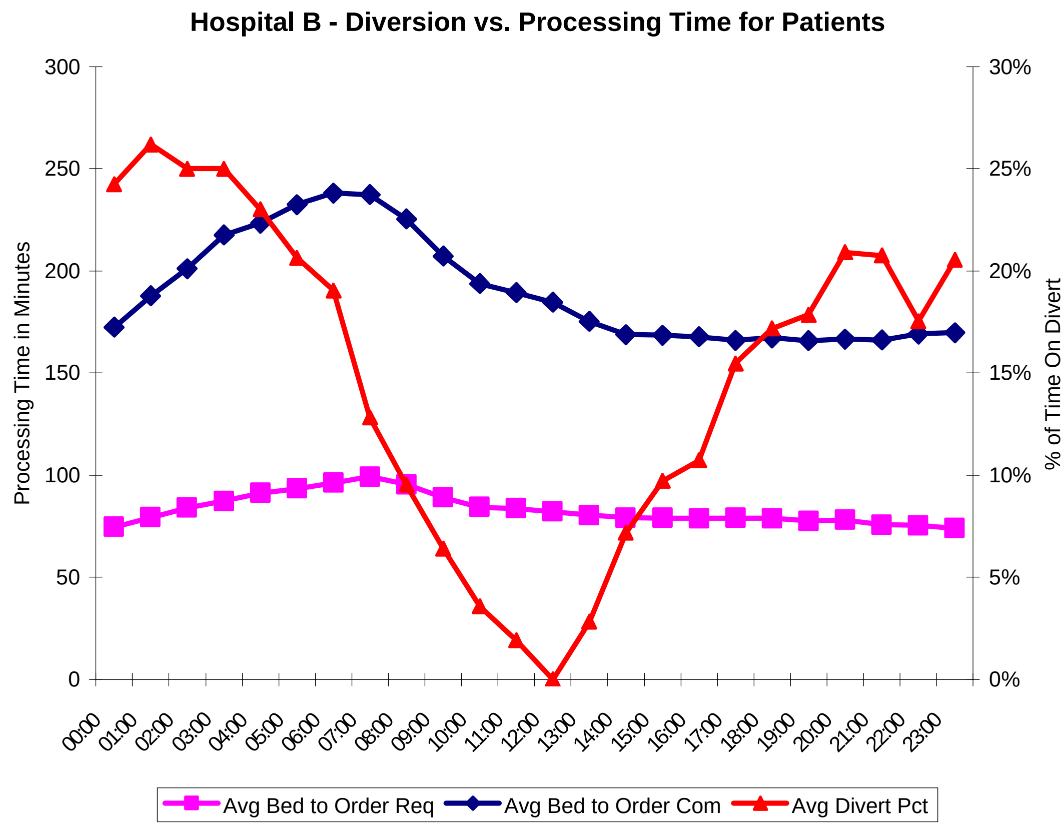

Fig. 17

Hypothesis #2 Conclusion:

The inverse relationship between processing time and diversion status, along with the lack of relationship on an hour of the day basis, indicate that processing time is not a significant driver of diversion status. While ED processing including the time it takes to complete inpatient orders has a small correlation to diversion status, it is our belief that even this small relationship is most likely a manifestation of decreased urgency surrounding completion of orders due to a lack of available beds rather than a cause of overcrowding in and of itself.

Hypothesis #3: ED arrival and processing rates are fine, but there are not enough beds in the hospital to accommodate the admissions.

Test: Correlate Avg. number of patients waiting for beds (boarding) in the ED vs. Diversion Status

Results:

The point-serial coefficient between the number of boarding patients in the ED and diversion status (r = 0.327) is substantially larger than the correlations found in the other hypotheses.

Comparing the average number of boarders during diversion hours (n = 167) and non-diversion hours (n = 840) reveals that the number of boarders during diversion hours is substantially higher (10.14 patients vs. 7.19 patients), meaning that on *average* there were 41% more patients boarding in the ED during diversion hours than during non-diversion hours.

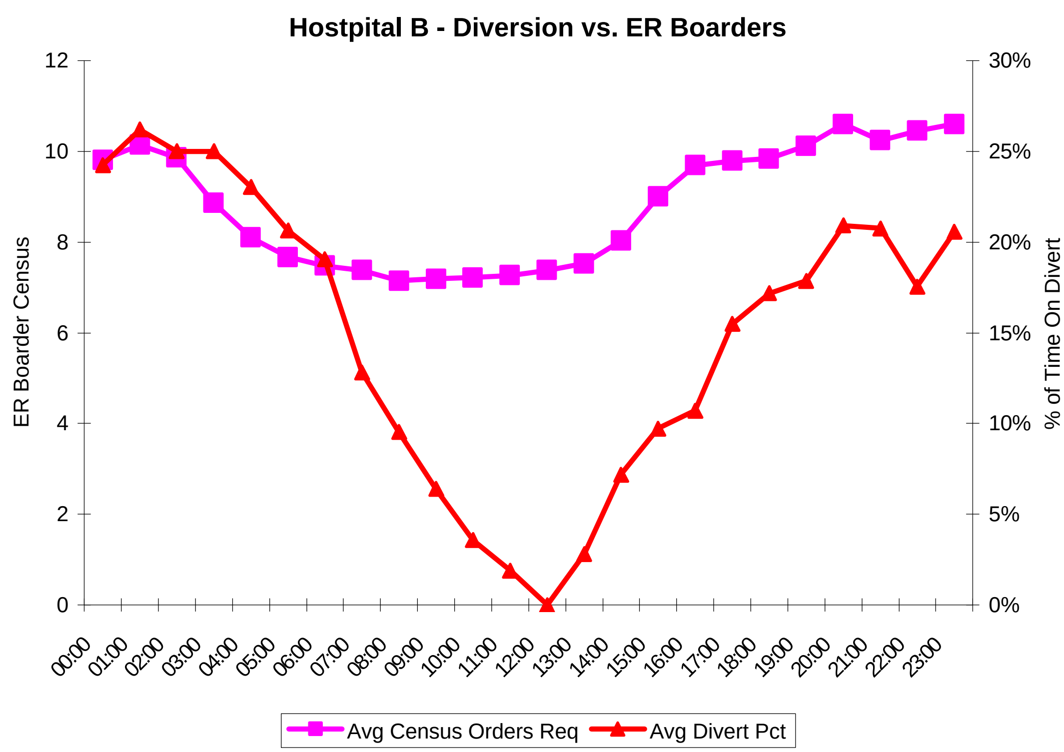

Fig. 18

Hypothesis #3 Conclusion:

Graphical representation of averages by hour of the day (see Fig. 18) are self-explanatory, and clearly indicate that as the number of patients boarding in the ED increases, so too does diversion. This result, along with the correlation of boarders to divert status and the average boarders while under divert status, again points towards examining hospital capacity as the primary determinate of diversion.

Census/Admissions/Discharges: Hospital B

The overall relationship between inpatient census and ED boarders in Hospital B was similar to that of Hospital A. However, detailed analysis of admission sources in Hospital B is not presented because scheduled demand played a far smaller role than that observed in Hospital A.

During the study period, there were 1,158 weekday unscheduled admissions (average: 38.6/day) and 208 weekday scheduled admissions (average: 6.9/day). This suggests very little operational flexibility in controlling the variability or timing of scheduled arrivals. This likely reflects a fundamental difference between most community hospitals and larger academic centers.

Hospital B Conclusions:

The findings at Hospital B are consistent with and reinforce those at Hospital A. Specifically, there was no evidence that ED process times were temporally or mechanistically related to ED diversion while the relationship between ED arrival rate and diversion was weak. Instead, the data suggest that factors outside of the ED that combine to increase boarders and limit ED capacity are more important.

Phase II Summary:

Detailed flow analysis in two very different types of hospitals yielded similar findings with respect to the root cause of emergency department crowding and ambulance diversion. Neither increased patient inflow nor increased process time could be strongly related to diversion status. Instead, diversion was seen as an outflow problem, with busy emergency departments crowding as patients await transfer to crowded inpatient services. This problem is exacerbated in hospitals with large volumes of scheduled admissions, since these necessarily compete for the same resources. The “collision” of scheduled and unscheduled patient flows results in diversion patterns that are specific and reproducible. Because scheduled patient flows are theoretically controllable, better understanding of this phenomenon may suggest means of decreasing diversion. If the experience here may be generalized, we conclude that institutions with small (or uncontrollable) scheduled patient flows will require addition of resources *on the inpatient side* if diversion is to be substantially reduced.

Phase III

Phase III of the investigation included mathematical and computer simulation modeling of patient flow within hospitals. The goal of this phase was three-fold:

1. Provide precise analytical description and verification of the relationships underlying the observational data acquired in Phase II.

2. Produce an instructional tool capable of reliably simulating the behavior of a simple hospital under changing conditions of supply, demand, and capacity.

3. Construct a platform for ongoing research into the interrelationship of hospital management and access to care.

Process structure was analyzed in both study hospitals with particular attention paid to patient flow. Service blueprints were then constructed covering all major process elements (from arrival to discharge) for both scheduled and unscheduled patients. Blueprints for the two institutions were then compared and common elements distilled for production of a “generic” hospital model. In the resulting generic model, multiple specialty services are collapsed into three types of inpatient units: medical/surgical, intensive care, and telemetry (monitored beds).

Obstetrical units, which rarely utilize emergency department, operating room, or general inpatient resources, are excluded from the model, as are all dedicated pediatric units. This was done because these units generally operate in a manner that is autonomous from the rest of the hospital. In addition, ancillary service areas that have only minor flows to inpatient services are combined within the “OR/Other” section of the model.

The stochastic nature of arrival and process times for each unit of each study hospital were then determined as follows. First, data obtained in phase II were entered into an online analytical processing (OLAP) cube for rapid retrieval of counts, averages and percentages. Arrival rates and process times were then examined in hourly increments across the entire study period and distributions observed by day of the week, hour of the day, site of entry, site of service, acuity level and disposition. The shape of each distribution curve was then determined qualitatively and quantitatively using curve-fitting software.

Patient flow attributes were then modeled mathematically using the above service blueprints and arrival/process distributions. As discussed earlier, it was ultimately determined that a computer simulation approach possessed advantages over analytical modeling techniques. A suitable modeling environment was then identified as the platform for development.

Service characteristics of the generic hospital were then converted to simulation processes and phase II data was utilized as inputs. Specifically, real arrival and service time data from the study hospital were used as inputs to the model and the following outputs observed: med/surgical bed utilization rate, telemetry utilization, ICU utilization, and average ED census. The model was considered satisfactory when outputs from multiple randomized runs differed from observed data by less than 5%.

To complete construction of the simulation model, input data from observations were replaced with the input standard distribution curves suggested by analysis of the observed data with curve fitting software. The advantage of this is that these standard distributions contain data in the "tails" which might not be captured in only six weeks of observation. Including the tails is intended to provide greater forecasting accuracy when longer periods are simulated.

To facilitate understanding of diversion, a feature was subsequently incorporated into the above model wherein the user may specify threshold conditions (e.g. number of boarders or patients in the ED waiting room) which will trigger diversion status. When these thresholds are exceeded, all new arrivals to the ED are rejected and further entry denied until hospital utilization parameters fall back within the specified limits. While this form of diversion is more rigid than the simple diversion of ambulances, it clarifies the understanding that all patients are put at risk when hospital saturation necessitates diversion. The full features and operation of the model are described in its documentation, provided with the model.

The resulting generic hospital flow simulator (the ED Divert Model©) was then used to test several hypotheses regarding diversion. Multiple scenarios were investigated, including increased ED demand, increased OR demand, various configurations of inpatient bed capacity and various changes in service times. While full presentation of sensitivity analyses is beyond the scope of this report, it may be confidently stated that the model was found to reflect the sensitivity of ED operations to inpatient resources, particularly ICU and telemetry beds.

Overall, the outflow hypothesis of ED diversion, as examined by hypothesis #3 in each of the hospitals above, was supported by simulation data as well. Under most conditions, the expansion of ED resources was seldom seen to diminish patient diversion and sometimes, paradoxically, increased it. This is because, as ED arrivals increase, bottlenecks appear on the inpatient side and ED outflow is slowed. As a result, queues for inpatient beds slowly choke any added ED capacity. In many cases, addition of inpatient resources stabilized or decreased diversion whereas addition of ED resources could not. One such scenario is illustrated in a model hospital containing 30 ED treatment sites, 110 inpatient medical/surgical beds, 50 telemetry or monitored beds and 25 intensive care beds facing a volume of ~20,000 emergency visits and ~7,000 scheduled and unscheduled direct admissions (via OR or other routes) annually. Under steady-state conditions, such an institution would demonstrate ED, Floor, Telemetry and ICU utilization rates of 63, 77, 96 and 98% respectively; not far from averages seen throughout Massachusetts. If ED volume were to increase further by just 5% (similar to the increase seen throughout Massachusetts over the past two years), ED utilization increases to 99% and waiting times for service rise exponentially. If, in response, the ED is expanded by 1/3 (to 40 beds), utilization decreases to 95% but queue lengths and waiting times remain unacceptably long (days). If, instead, the ICU is expanded by 10% (to 28 beds) and the ED left unchanged, ICU utilization remains high (91%) but ED utilization is nearly halved! This counter-intuitive finding becomes understandable when model outputs disclose that ED overload was, in fact, a consequence of inpatient bottlenecks and the types of admissions encountered rather than ED saturation per se.

It is important to note that while variability methodology was employed in its conceptualization and design, the model in its present configuration is incapable of simulating different degrees of schedule “smoothing”. This is because smoothing requires specific assumptions and tradeoffs that would vary considerably from hospital to hospital. Due to the nature of the modeling environment, these assumptions cannot be simply layered onto a generic model and must instead be incorporated into the basic design of future, hospital-specific versions.

Study Analysis and Findings - Conclusions

This study found that the most significant driver of ED diversions in the two hospitals studied is the lack of sufficient inpatient capacity. This is supported both by observational data and by stochastic modeling. Capacity shortfalls may result from either an *absolute* lack of staffed hospital beds, a *periodic* bed shortage revealed during peaks of demand, or a combination of the two. The relative importance of these two factors varies between different hospitals and should be determined based on analysis of the demand and capacity data for both scheduled and unscheduled admissions for each particular hospital. A larger-scale study of the capacity, demand, and variability issues would be necessary to adequately address the root causes of ED diversions in a broader cross-section of hospitals. A more extensive sampling would also permit development of a more robust computer model.