



**HOSPITAL PERFORMANCE IMPROVEMENT:  
TRENDS IN QUALITY AND EFFICIENCY**  
**A QUANTITATIVE ANALYSIS OF PERFORMANCE IMPROVEMENT  
IN U.S. HOSPITALS**

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April 2007

**ABSTRACT:** This report presents results of a quantitative examination of the dynamics of hospital performance: the degree to which hospitals are improving (or deteriorating) in quality and efficiency over time. Results indicate significant improvements across hospitals in reducing mortality and increasing efficiency over 2001–2005, with mixed results in complication and morbidity rates. Reduced mortality is likely due to improvements in care, such as better diagnostic techniques and earlier interventions, as well as more conscientious record “coding” and changing discharge practices. Consistent reductions in length of stay underscore the financial pressures on hospitals, perhaps combined with improved ability to stabilize, treat, and discharge patients. The characteristics of the most-improving hospitals indicate that quality improvement is immanently attainable, occurring at least as much among small, non-teaching institutions as among their larger, more prominent counterparts. A companion report, [\*Hospital Quality Improvement: Strategies and Lessons from U.S. Hospitals\*](#), presents case studies of four top-improving hospitals identified in this analysis.

Support for this research was provided by The Commonwealth Fund. The views presented here are those of the authors and not necessarily those of The Commonwealth Fund or its directors, officers, or staff. This report and other Fund publications are available online at [www.cmwf.org](http://www.cmwf.org). To learn more about new publications when they become available, visit the Fund’s Web site and [register to receive e-mail alerts](#). Commonwealth Fund pub. no. 1008.



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## ACKNOWLEDGMENTS

The authors gratefully acknowledge the support of The Commonwealth Fund, and the guidance of Anne-Marie Audet, M.D., and Anthony Shih, M.D. We also thank the following experts who advised us during the course of this study, and whose insights and suggestions were invaluable:

Diane L. Bechel Marriott, Dr.P.H., pharmacy benefit manager,  
Ford Motor Company

Stuart Guterman, senior program director, The Commonwealth Fund

Ashish Jha, M.D., M.P.H., assistant professor, Harvard School of Public Health

Andrea Silvey, Ph.D., M.S.N., chief quality improvement officer,  
Medicare QIO of Arizona Health Service Advisory Group

## EXECUTIVE SUMMARY

Since the Institute of Medicine's landmark reports, *To Err Is Human* (2000) and *Crossing the Quality Chasm* (2001), revealed widespread incidence of medical errors and substandard care in U.S. hospitals, there has been a great deal of effort to measure and improve the quality of hospital care.<sup>1</sup> Much progress has been made in developing quality indicators and risk-adjustment mechanisms to compare quality across institutions, and in examining practices and cultures in high-performing hospitals. Little is known, however, about the dynamics of hospital performance: the degree to which hospitals are improving (or deteriorating) over time, and how they achieve and sustain that improvement. This report presents the findings of a quantitative analysis of quality and efficiency trends using three hospital databases. A companion report, [\*Hospital Quality Improvement: Strategies and Lessons from U.S. Hospitals\*](#), presents results of case study analysis of four hospitals that experienced significant improvement on a composite quality indicator based on risk-adjusted mortality, complication, and morbidity rates.

We found significant improvements in mortality rates broadly across hospitals, likely indicating that hospitals have been getting better at keeping people alive through error reduction, improved technologies, adherence to evidence-based protocols, and other strategies. The improved mortality scores may also be attributed in part to more conscientious “coding” of comorbidities, and to discharging of sicker patients who may expire in home or hospice settings.

### **PERFORMANCE TRENDS AMONG ACUTE CARE HOSPITALS: QUANTITATIVE ANALYSIS SUMMARY**

An analysis of three different acute care hospital databases over three-year periods between 2001 and 2005 reveals major improvements in risk-adjusted mortality and efficiency, but mixed results for complications and morbidity. Using public all-payer hospital data from 12 states, Medicare data from all states, and extensive administrative and clinical data from a group of client hospitals for CareScience, Inc., we compared the number of hospitals that illustrated steady, significant improvements in risk-adjusted measures of quality and efficiency with those showing steady, significant declines, or “deterioration.”<sup>2</sup> (See [Appendix](#) for description of methodology.)

#### **Improved Mortality Rates**

Substantial reductions in mortality rates across all databases are a consequence of a falling actual “raw” mortality rate and rising mortality risk. The falling raw rate suggests that hospitals are indeed becoming better at saving lives through better diagnostic techniques,



early interventions, better treatments, more effective rescue efforts, reductions in errors, and other initiatives. The trend also may be attributed in part to changing discharge practices, with more deaths occurring outside of hospitals (e.g., in hospices, long-term care facilities, or homes) or during subsequent hospitalizations. The rising risk suggests that hospital patients are sicker. Factors such as the aging population, rising prevalence of chronic conditions, and the growing delivery of minor surgery on an outpatient basis reduce the proportion of low-risk inpatients and raise the proportion of more complicated and severe inpatients. It also may be true that hospitals are coding patients and conditions more conscientiously and completely, which raises the risk factor. Further investigation in this area is warranted.

### **Improved Efficiency**

Length of stay (LOS), though not a full measure of cost, is an indication of resource usage and used as a rough proxy for efficiency in this study. A steady, significant reduction in risk-adjusted LOS over time seems primarily to reflect ongoing financial pressures on hospitals to reduce costs. This also may signify improved ability of hospitals to stabilize patients more quickly, or a trend toward discharging patients earlier and caring for them in outpatient, home, and other non-hospital settings. The former would be consistent with more efficient care, whereas the latter would not reflect either greater or lesser hospital efficiency.

One possible negative consequence of the ongoing reduction in LOS is the release of patients before they are truly ready for discharge, and/or without adequate follow-up home care in place—an issue that has been studied and should continue to be explored as hospital dynamics and forces change. Our study, however, casts doubt on the idea that declining length of stay as well as improved mortality rates reflect discharge of sicker patients that results in more readmissions. An examination of the CareScience private data (the public databases do not permit examination of readmissions) shows a basically flat readmission trend line, suggesting that the readmission rate has not significantly changed in the three years studied.

### **Mixed Trends**

Trends in complications and complication morbidity (or simply “morbidity” in this report, defined as severe complications) were mixed. Complication rates improved but morbidity rates deteriorated in the two public databases, and the reverse trend was seen among the third group based on CareScience private data.<sup>3</sup> Possible reasons, discussed further below, include differences in the measurement of observed rates and inferred risks for both complications and morbidity between the public and private databases (Table ES-1).

Table ES-1. Summary Trends in Risk-Adjusted Hospital Quality and Efficiency Measures

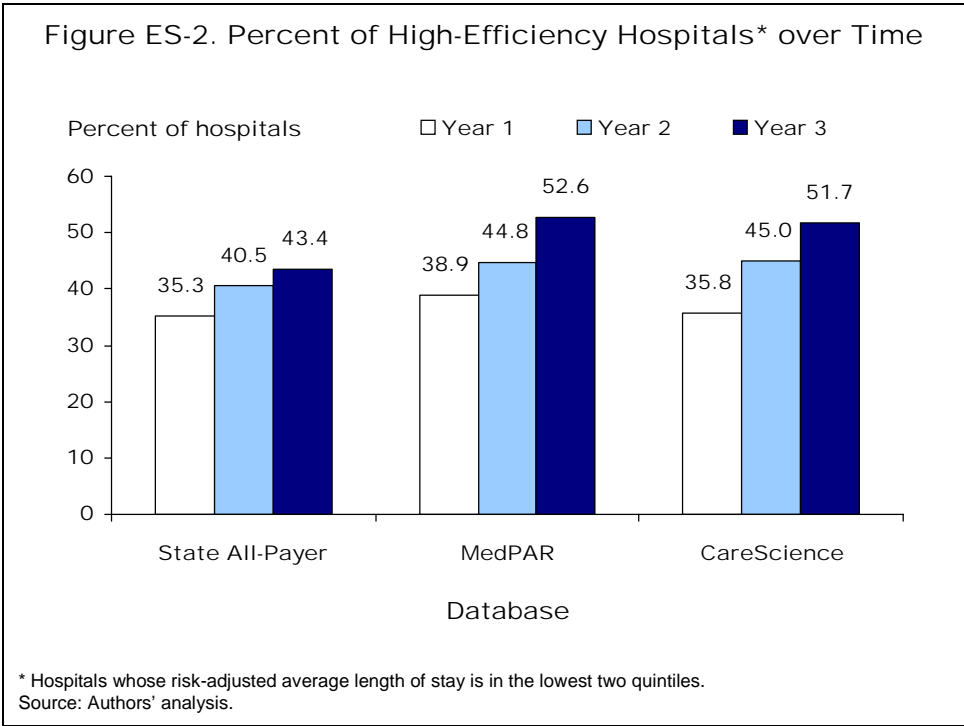
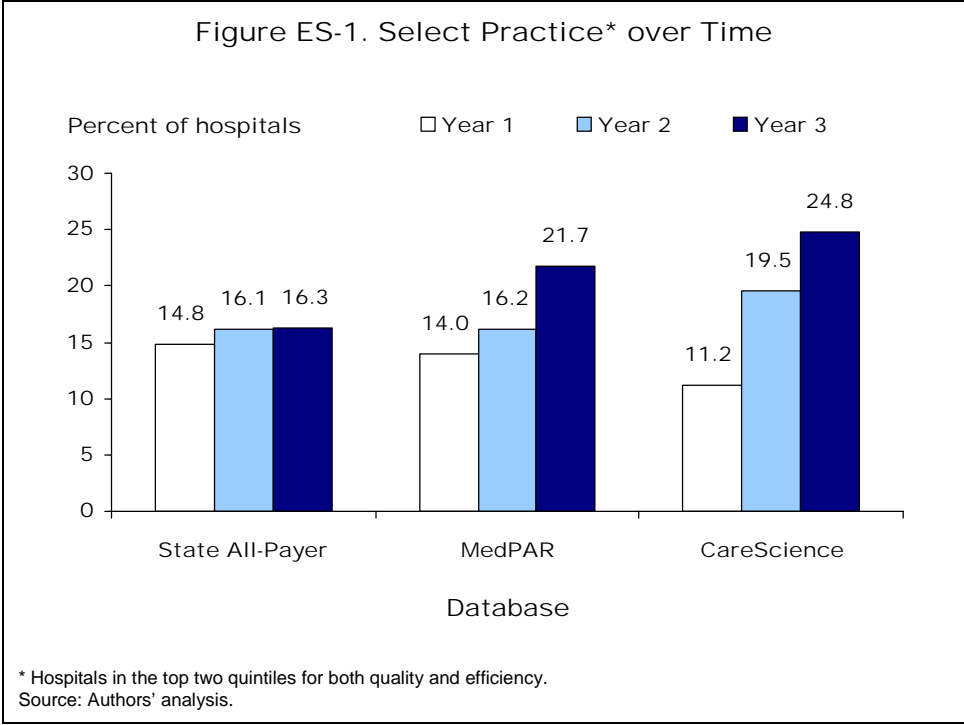
Hospital Database	State All-Payer n=1090	MedPAR n=2943	CareScience Private Data n=149	Average*
Three-year time period studied	2001–2003	2002–2004	2003–2005	
<b>Mortality</b>				
% steadily improve vs. deteriorate	Improvement 40% vs. 7%	Improvement 37% vs. 5%	Improvement 53% vs. 3%	Improvement 43% vs. 5%
<b>Complications</b>				
% steadily improve vs. deteriorate	Improvement 35% vs. 27%	Improvement 37% vs. 20%	Deterioration 17% vs. 36%	Improvement 30% vs. 28%
<b>Morbidity</b>				
% steadily improve vs. deteriorate	Deterioration 6% vs. 61%	Deterioration 10% vs. 39%	Improvement 42% vs. 9%	Deterioration 19% vs. 36%
<b>Efficiency**</b>				
% steadily improve vs. deteriorate	Improvement 55% vs. 17%	Improvement 62% vs. 9%	Improvement 55% vs. 13%	Improvement 57% vs. 13%

\* Readers should be cautious about citing this arithmetic average, since it reflects three different but overlapping sets of hospitals, time periods, and measures. It is presented here to summarize the findings only.

\*\* Efficiency is measured as risk-adjusted length of stay.

Using a composite measure that designates hospitals showing both high quality and high efficiency as “Select Practice,” our analysis shows that the portion of Select Practice hospitals increased over the study periods. (In Select Practice analysis, the quality component is an amalgam of mortality, morbidity, and complications; and length of stay is used as a proxy for efficiency. The methodology behind Select Practice designation is outlined in the “Setting” section that follows and described in detail in the [Appendix](#).) Select Practice hospitals were most likely to retain their high-performing status from year to year. There was also steady decline in poor-performing (low quality, low efficiency) hospitals over time. In one data set (MedPAR), the number of hospitals in the low-quality and low-efficiency group fell by more than one-third in just one year, a stunning change.

Disaggregation of our findings indicates that the increase in Select Practice hospitals was driven primarily by improvements in efficiency. There was a strong, steady movement toward “high efficiency” hospitals in all of the databases studied, again indicating consistent pressures on hospitals to reduce costs (Figures ES-1 and ES-2). Movement of hospitals into a “high-quality” category (regardless of LOS) is less pronounced and mixed across the databases studied, likely reflecting the inclusion of morbidity and complication rate indicators (which were mixed) along with the mortality indicator (which clearly showed an improvement trend in all databases) in the quality measure.



**Characteristics of High Improvers**

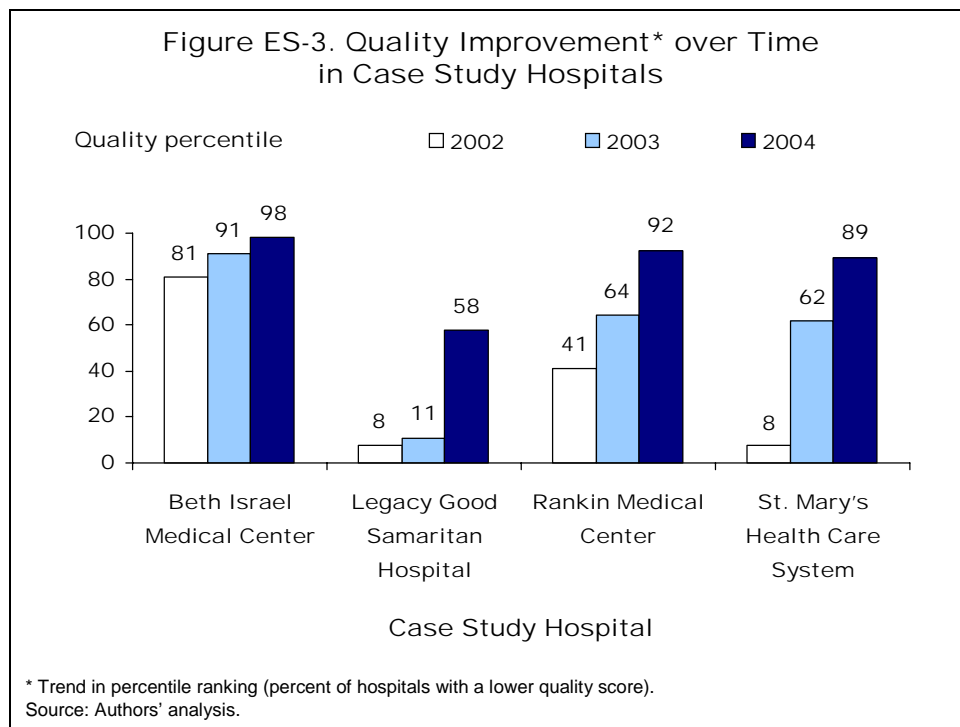
Contrary to widely held beliefs that the biggest strides in quality improvement would occur at large, teaching hospitals, our analysis found that most-improving hospitals in quality tend to be smaller than average size (even after excluding the smallest hospitals),

and less likely than other hospitals to be major teaching institutions.<sup>4</sup> That is, the results indicate that quality improvement is quite attainable at hospitals that are not the “usual suspects.” Most-improving hospitals in efficiency, however, are more likely to be major teaching institutions.

Not surprisingly, hospitals showing the greatest jump in quality most often began at the very lowest end of the quality spectrum, suggesting they jumped because they had the most room to improve. Conversely, hospitals showing greatest deterioration most often began at the top level; they had most room to fall. In addition to a general improvement in performance over time, there appears to be some temporal regression toward the mean.

### Four Case Study Hospitals

A companion report, [Hospital Quality Improvement: Strategies and Lessons from U.S. Hospitals](#), includes case studies of four hospitals that were among the highest improvers, describing their particular strategies and challenges and outlining a shared quality improvement process. Figure ES-3 illustrates the significant improvement in quality rankings for the case study hospitals: Beth Israel Medical Center; Legacy Good Samaritan Hospital; Rankin Medical Center; and St. Mary’s Health Care System. The percentiles signify ranking within each year among the nearly 3,000 acute care hospitals in the MedPAR database, after excluding hospitals with fewer than 850 annual discharges.



# HOSPITAL PERFORMANCE IMPROVEMENT: TRENDS IN QUALITY AND EFFICIENCY

## A QUANTITATIVE ANALYSIS OF PERFORMANCE IMPROVEMENT IN U.S. HOSPITALS

### STATEMENT OF PURPOSE

Despite much excellent research in recent years, there appears to be a gap in knowledge about widespread changes over time in performance at the hospital level. The objective of this study was to use a combination of quantitative and qualitative research to gain a better understanding of the dynamics of hospital performance. We sought to examine patterns of hospital quality and efficiency over time and identify approaches that have been successful in improving health outcomes. The goal was to produce information that could be used to improve hospital performance across the country.

Researchers at Health Management Associates and CareScience, Inc., worked together to design and conduct quantitative analysis of three hospital databases covering 2001–2005. (The results of the qualitative, case study analysis of four selected “high-improving” hospitals are presented in a companion report, [\*Hospital Quality Improvement: Strategies and Lessons from U.S. Hospitals.\*](#)) We attempted to answer the following questions:

- What proportion of hospitals experienced a substantial improvement in quality and efficiency in recent years, and what proportion lost ground?
- What are the patterns of improvement or deterioration for the individual components of quality as defined by risk-adjusted mortality, morbidity, and complication rates? Are there similar patterns across databases and time periods?
- Do the hospitals that have shown most improvement share characteristics, such as size, teaching status, or region?
- Is there a considerable amount of fluctuation, as when hospitals improve in one year but decline in the next or vice versa, without any particular trend developing?
- When examining a composite measure of value, is most of the improvement seen attributable to better quality care, or reduced costs?
- What do these results tell us about the success of quality improvement efforts, and the need for further efforts to improve performance?

## **HYPOTHESES**

Based on our own preliminary work and a review of the literature (summarized in the companion report),<sup>5</sup> we hypothesized that, as a general trend, hospitals would have improved in terms of both quality and efficiency in recent years since there has been great attention to the issue of poor quality and high costs in health care and as clinical guidelines, evidence-based medicine, and quality-enhancing technologies have begun to be widely disseminated. That is, the lessons learned and best practices developed by the early leaders in the field may have been made available to and accepted by other hospitals.

We also hypothesized that most of the improvement in terms of value would be attributable to better quality and that efficiency, when measured by length of stay (LOS), would play a smaller role. This is because LOS may already have been squeezed considerably by the starting point of this analysis (2001), whereas there has been much recent research and activity focusing on quality measurement and interventions.

## **SETTING**

Outcome comparisons among providers have been viewed as a potentially effective way to motivate improvement in the quality of care. Like health care providers, payers and consumers are interested in the evaluation of clinical practice across hospitals within both disease and physician groups. Such comparisons are often called practice profiles, outcome reports, report cards, or scorecards. No single standard measure of effectiveness of care is universally acceptable, but certain key elements are common to these measures.

Mortality is a widely used measure of quality of care, but it alone does not cover all dimensions of quality. In the CareScience model used in this analysis, quality is measured by the incidence of three adverse outcomes: mortality, morbidity, and complications. The morbidity rate is distinguished from the broader complication rate in focusing on severe and clinically significant complications (and, hence, a subset of all complications). Severe and clinically significant (morbid) complications cause a major departure from the standard course of treatment, usually requiring an unscheduled intensive care unit stay and associated with a significant risk of major organ failure. The designation is based on expert clinical judgment applied to the secondary diagnosis in question in relation to the patient's principal diagnosis.<sup>6</sup> The three indicators, though related, are not highly correlated, as evidenced both in this study and in the Corporate Hospital Rating Project.<sup>7</sup> To provide a broad, robust performance indicator, they are combined into a single quality measure using the preference weightings from the Corporate Hospital Rating Project.

Under the Institute of Medicine framework, a highly performing hospital should deliver effective health care in an economically efficient way.<sup>8</sup> In the CareScience rating model, the efficiency is calculated based upon LOS as a proxy for resource usage. It reflects general efficiency in hospital care delivery, thereby serving to approximate how efficiently a hospital allocates resources among patients.

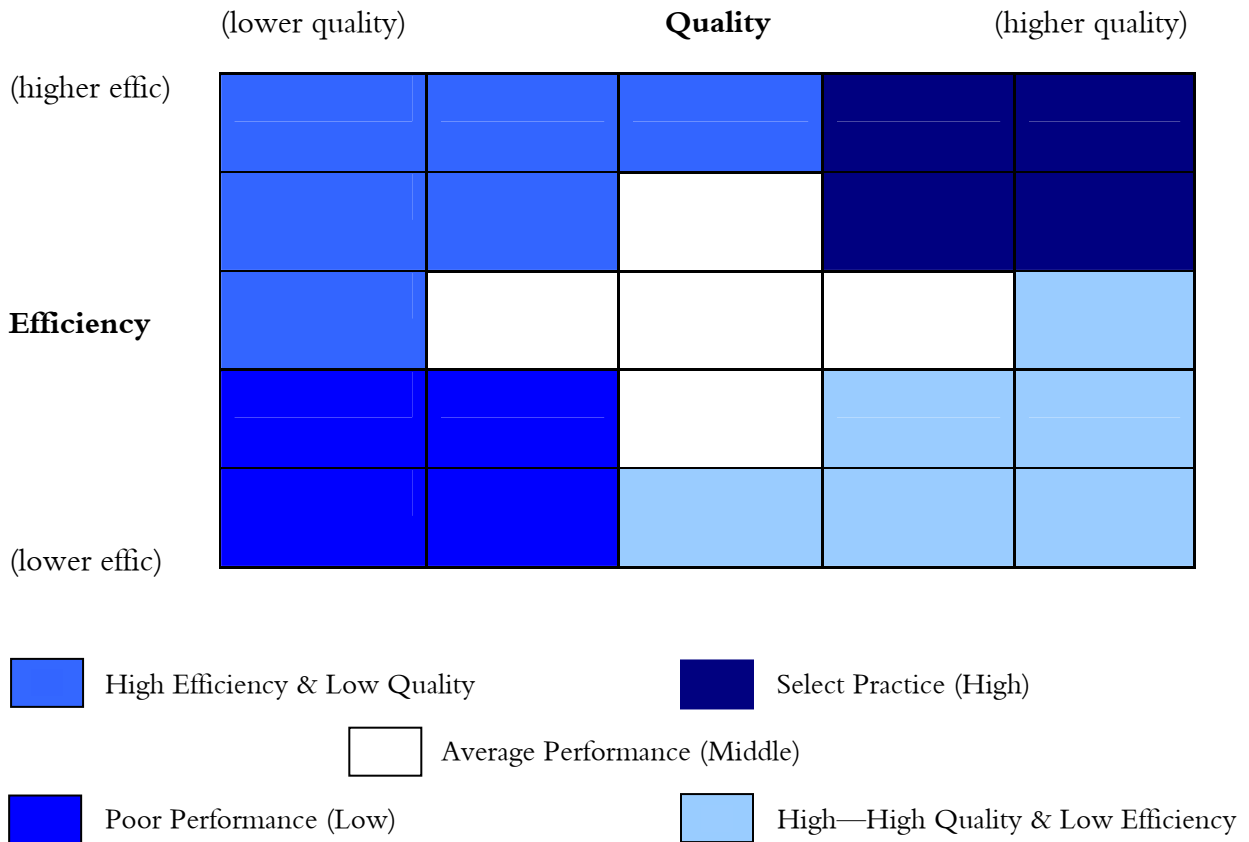
### **Risk Adjustment**

Meaningful comparisons of outcomes among providers must take into account systematic variation in the patient mix across providers. Patient-specific risk adjustment is a widely used method to provide a common ground for these comparisons. A risk-assessment model provides a mechanism for any provider's outcomes (mortality rates, morbidity rates, complication rates, average length of stay, and cost per case) to be compared to expected outcome rates (outcome risks) derived from its case mix. This study's risk adjustment model is described in the [Appendix](#). By identifying and isolating outcome variation attributable to patients, providers with different case mixes can be compared in a statistically rigorous manner.

### **Select Practice—A Two-Dimensional Framework**

Hospitals in this study are ranked separately for quality and efficiency (length of stay), with the highest rankings going to hospitals with the lowest risk-adjusted LOS and adverse outcome rates. To be classified as "Select Practice," a facility must be in the top two quintiles for both efficiency and quality. Because this rating system is two-dimensional, it does not explicitly trade off quality and efficiency. The five-by-five efficiency/quality matrix is illustrated in Figure 1. In this study the rankings are only weakly correlated (i.e., they are fairly evenly distributed across the grid). Select Practice facilities ("High") constitute 16 percent (40% of 40%) of all that qualify for ranking. At the other end of the spectrum are the bottom two quintiles for both efficiency and quality (four poor performance "Low" cells). Three other designations cover the mid-ranges: average performance of the "Middle" five cells, six low-quality/high-efficiency cells, and the opposing six high-quality/low-efficiency cells.

Figure 1. Five Performance Categories Based on CareScience Select Practice



Select Practice is a trademark of CareScience, a division of Quovadx, Inc.

### Performance Trends

In order to track the changes in hospital performance over a certain time period, the first year is treated as the starting point and the third year the ending point. For individual outcomes, each trend in the risk-adjusted measure is classified into one of three categories: decreasing, flat, or increasing. A decreasing risk-adjusted outcome (including mortality, morbidity, complications, LOS) signals performance improvement. In each category, the time pattern is observed as either steady or non-monotonic (both increasing and decreasing over subperiods of the three-year time span).

If the difference (last year minus first year) is statistically significant at a minimum of 95 percent confidence, greater than about two standard errors in this case, the hospital is designated to have had deterioration in outcome performance. By the same argument, if the difference is less than the negative of two standard errors, the hospital reflects a performance improvement. Within those critical values, the outcome performance has not changed significantly and is designated “flat.” Depending upon the performance scores in the middle year, using the same critical values for statistical significance, the time trend is



noted as either steady (moving continuously in one direction over the three years), up–down (“A” shaped), or down–up (“V” shaped). Because strong trends are most reliably reflected among the steady patterns, findings are based primarily on such results.

A hospital’s position in the Select Practice grid is tracked over a three–year time span as well. Hospital performance may move along a quality dimension, efficiency dimension, or some combination of the two. Select Practice represents the pinnacle of performance, where both quality and efficiency are at the highest levels.

## **Data**

Three databases are used in this study (described further in the [Appendix](#)):

- MedPAR (Medicare Provider Analysis and Review): based on Medicare inpatient data made available from the Centers for Medicare and Medicaid Services (CMS), covering 2002, 2003, and 2004. After excluding very small and non–acute institutions and those with incomplete data, our sample included 2,943 hospitals.
- State All–Payer Data: based on all patient records from hospitals in various states for the years 2001, 2002, and 2003. After being filtered to exclude very small and non–acute institutions and those with incomplete data, this sample included 1,090 hospitals from 12 states.
- CareScience Private Data: collected in compliance with its “Master Data Specification” (MDS), this database includes detailed elements spanning 2003, 2004, and 2005 for 149 hospitals.

## **FINDINGS**

### **Hospital Performance Characterizations**

Although the three data sets cover different time spans within the period from 2001 to 2005, the quality and efficiency measures share common performance traits when measured by the proportion of hospitals that are either improving or deteriorating. In particular, all three data sets are dominated by hospitals that exhibit strong declines (improvement) in risk–adjusted mortality rates and shorter lengths of stay over time. Table 1 presents outcomes for hospitals with steady trends only—i.e., continuing movement in the same direction over the three years studied, whether improvement (decrease in mortality, complications, morbidity, or LOS from year to year), “flat” (no significant change from year to year), or deterioration (increase in the indicator from year to year). More detailed tabulations that present inconsistent patterns (decrease–increase–decrease or vice versa) are found in the [Appendix](#).

Table 1. Steady Trends in Mortality, Complications, and Morbidity

<b>Hospital Database</b>	<b>State All-Payer n=1090</b>	<b>MedPAR n=2943</b>	<b>CareScience Private Group n=149</b>
Time period	2001–2003	2002–2004	2003–2005
<b>Mortality</b>			
Improvement	40.2%	37.1%	53.0%
Flat	35.0%	41.3%	24.8%
Deterioration	6.9%	4.7%	3.4%
<b>Complications</b>			
Improvement	34.5%	37.3%	16.8%
Flat	11.8%	19.5%	14.8%
Deterioration	27.3%	20.2%	35.6%
<b>Morbidity</b>			
Improvement	5.5%	10.3%	42.3%
Flat	17.2%	29.1%	22.8%
Deterioration	60.6%	38.9%	8.7%
<b>Length of Stay</b>			
Improvement	55.0%	62.4%	55.0%
Flat	5.7%	11.1%	4.7%
Deterioration	16.6%	8.9%	13.4%

Note: Distributions for each measure do not add to 100% because percentages of hospitals showing inconsistent patterns are not included.

While the time trends for mortality and length of stay are largely consistent across all three data sets, some divergences are found in the complication and morbidity trends. In particular, hospitals in which morbidity rates are improving are dominant in the CareScience private data set, whereas hospitals in which morbidity rates are deteriorating dominate both public data sets. The opposite is true for complication rates, for which a deterioration trend dominates in the CareScience data hospitals, while hospitals in which complications rates are improving dominate both public data sets. Possible reasons for this divergence include differences across the data sets in time range, limits in secondary diagnoses documented, and patient data elements (discussed further in the [Appendix](#)).

### **Quality and Efficiency Index Trends**

On the Select Practice grid (Figure 1), hospitals generally move toward higher quality and higher efficiency over time. Table 2 documents a steady increase in the number of hospitals in the most desirable Select Practice group (high quality and high efficiency), and a steady decrease in the number of hospitals in the least desirable group (low quality and low efficiency). Hospital trends toward greater efficiency are somewhat more pronounced

than those along the quality dimension. Moreover, these general trends toward improved performance are shared across all three data sets.

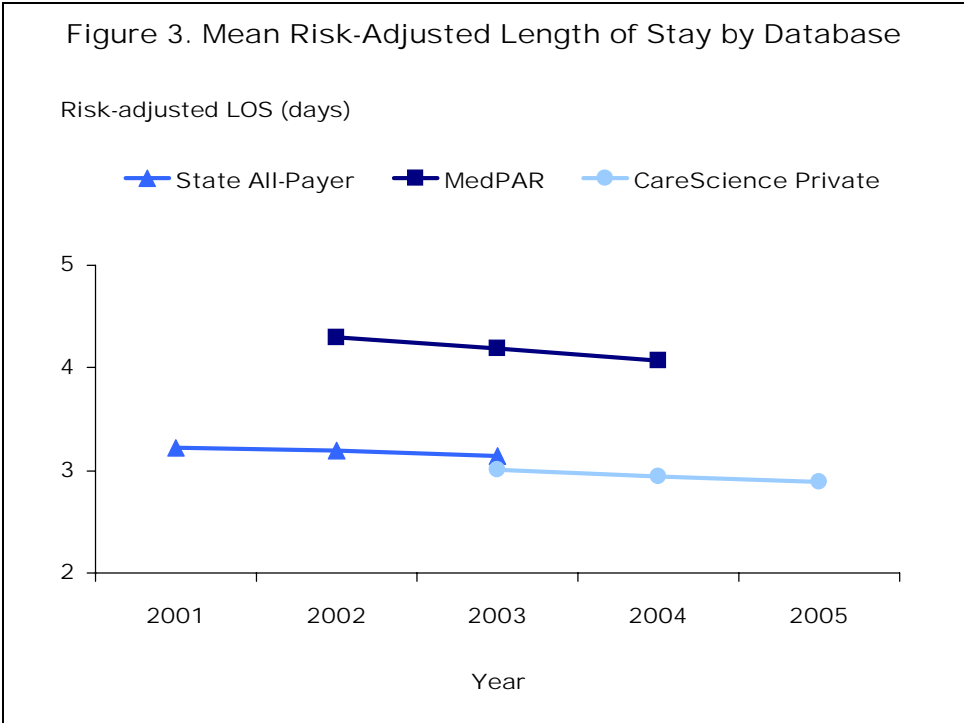
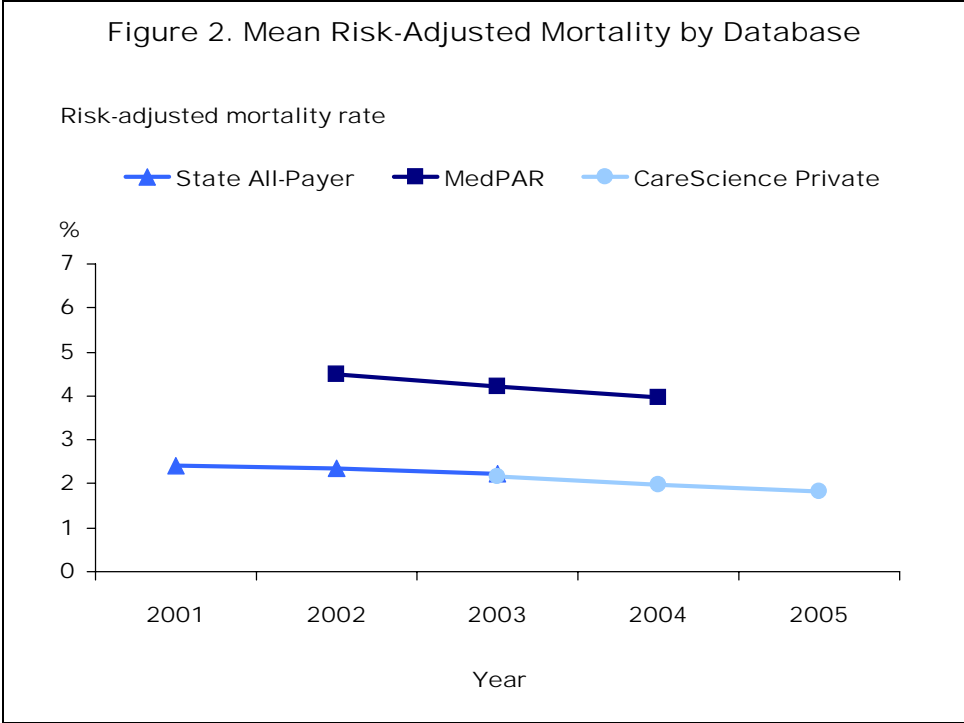
Table 2. Hospital Performance by Quality and Efficiency

Quality	Efficiency	State All-Payer			MedPAR			CareScience Private		
		2001	2002	2003	2002	2003	2004	2003	2004	2005
High	High	14.8%	16.1%	16.3%	14.0%	16.2%	21.7%	11.2%	19.5%	24.8%
Mid.	Mid.	19.8%	18.8%	20.5%	17.6%	18.5%	18.2%	20.1%	14.8%	14.8%
High	Low	29.9%	27.7%	24.2%	24.8%	21.5%	21.1%	21.6%	25.5%	19.5%
Low	High	20.6%	24.4%	27.1%	24.9%	28.6%	29.1%	24.6%	25.5%	26.8%
Low	Low	15.0%	13.0%	11.9%	18.7%	15.2%	9.9%	22.4%	14.8%	14.1%
N =										
Number of Hospitals		1090	1090	1090	2943	2943	2943	134	149	149

On the two-dimensional Select Practice grid, MedPAR data showed a similar trend as state all-payer data. Because the MedPAR data span a more recent period and include 2004 discharges, the comparison of two data sets is not ideal. But the changes from 2002 to 2003 in the MedPAR data do mirror the changes in the state data set for the same time period. From 2003 to 2004 there was a significant increase of hospitals in the high quality and high efficiency group. Hospitals in the low quality and low efficiency group fell by more than one-third in just one year, a stunning change.

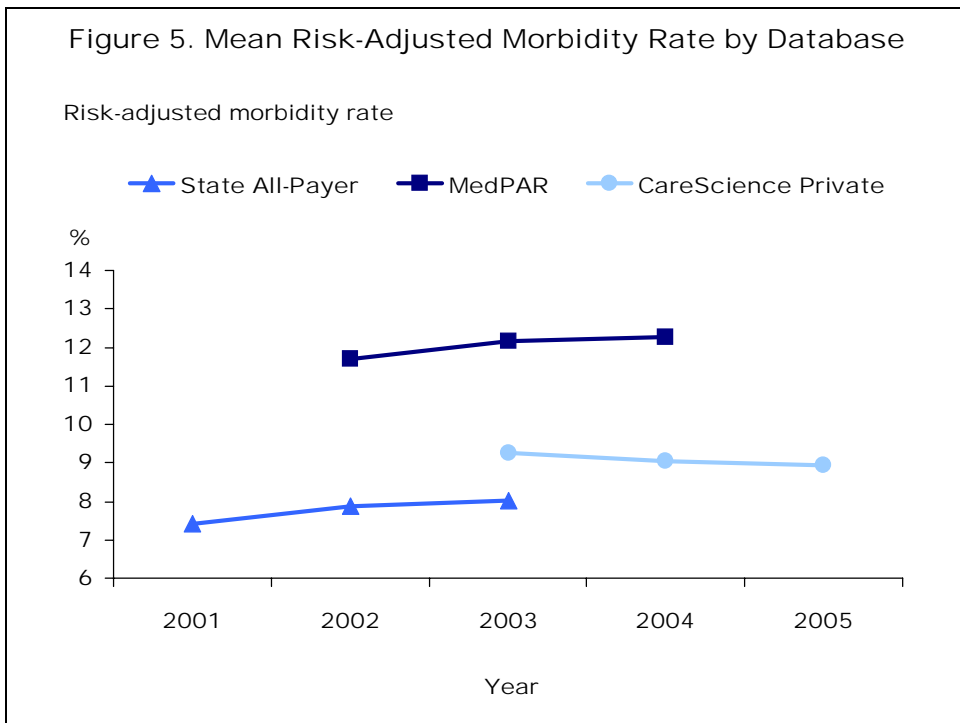
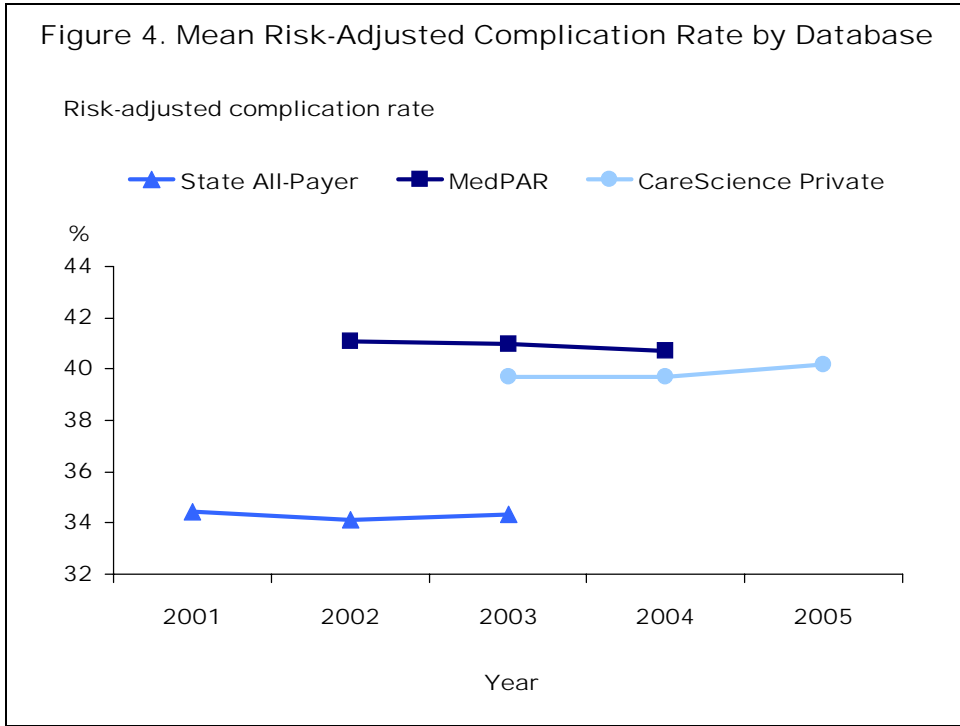
### Average Trends by Outcome

Breaking the trends down by individual outcome provides definition to the picture of movement in the quality and efficiency arena. The picture for risk-adjusted mortality and length of stay is unambiguous across all databases, as depicted in Figures 2 and 3. Medicare patients show higher mortality rates and length of stay than the general population, as expected, but the downward trends are quite similar: per annum average declines in risk-adjusted mortality of 6 percent among Medicare patients bracketed by 4 percent declines in the state data and 8 percent declines in the CareScience private data, and per annum average declines in length of stay of about 2 percent in all three data sets.



The trends in complications and morbidity are somewhat mixed for the reasons stated above and detailed in the [Appendix](#). Figure 4 shows that risk-adjusted complications are almost flat in the public data and rising slightly in the CareScience private data, at

about half a percent per year. Figure 5, by contrast, shows a distinctly rising trend in risk-adjusted morbidity in the public data (4% per year in the state data and 2.5% in MedPAR), but a steady decline of about 2 percent per year in the CareScience private data.



### Trend Dispersion by Outcome

The summary indicates that the greatest jumps in quality, both improvements and deteriorations, are dominated by hospitals in the extremes of the quality/efficiency distribution. This observation suggests a hypothesis of convergence in risk-adjusted outcomes over time. Standard F-tests and other related likelihood ratio tests for differences in dispersion over time are unable to reject the null hypothesis of constant dispersion (no convergence). These results are illustrated in Figures 6 through 9, which depict risk-adjusted outcomes for the top, middle, and bottom quintile of the distribution across hospitals in the MedPAR data. Measured as the percent change in the inter-quintile difference over the three-year span, the figures show virtually no convergence in risk-adjusted mortality and complication rates, and slight convergence in risk-adjusted morbidity (8%) and length of stay (10%).

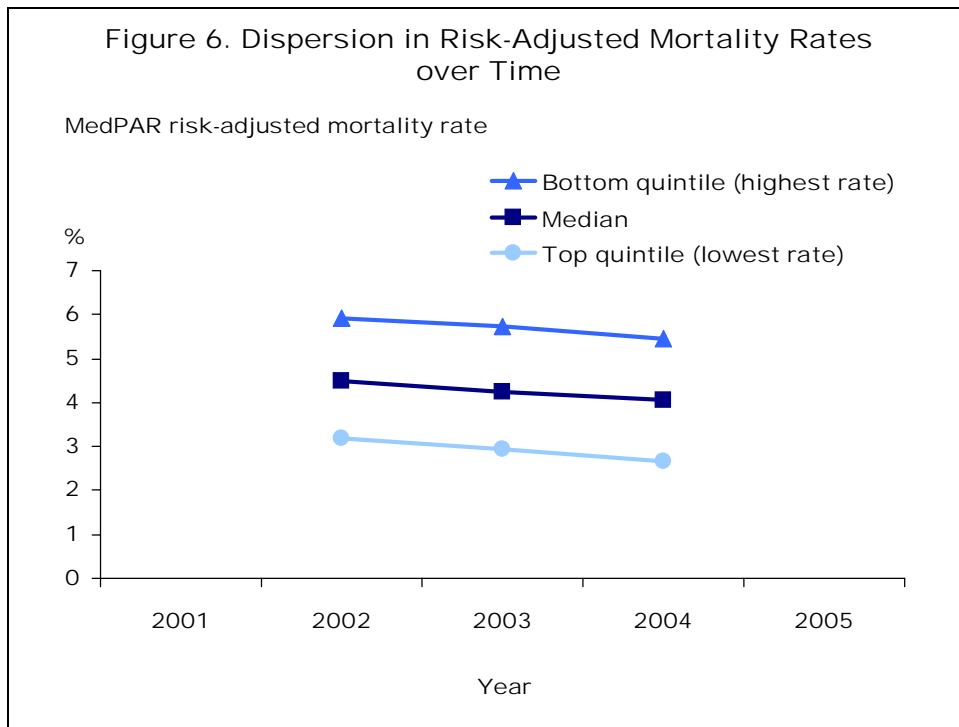


Figure 7. Dispersion in Risk-Adjusted Complication Rates over Time

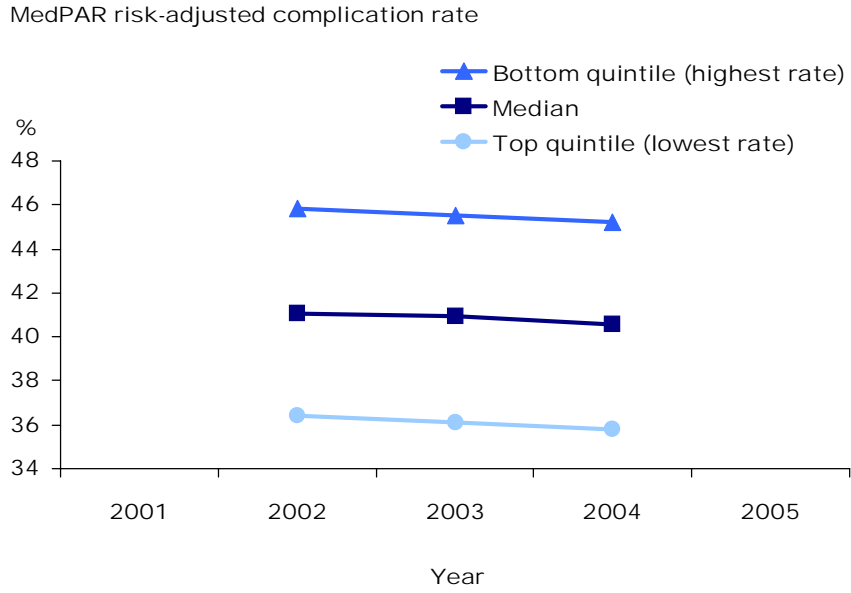
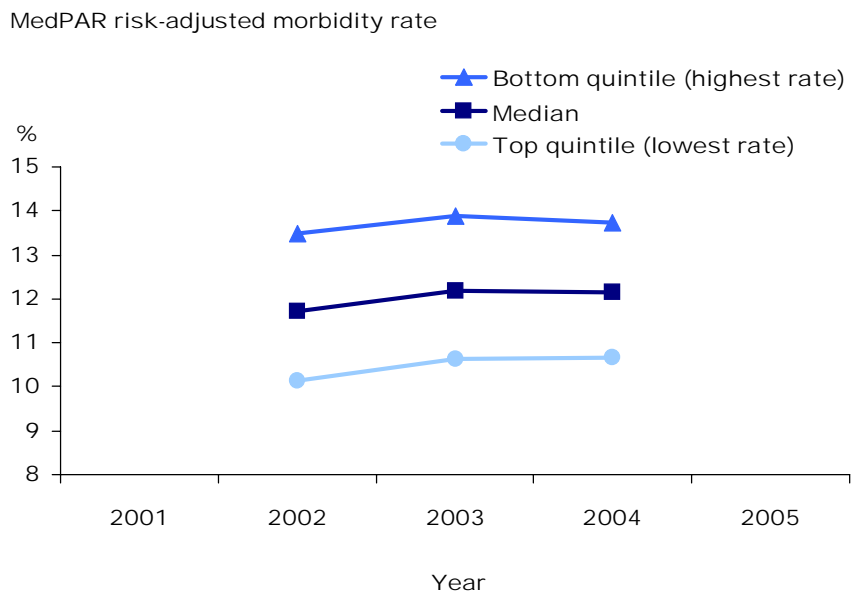
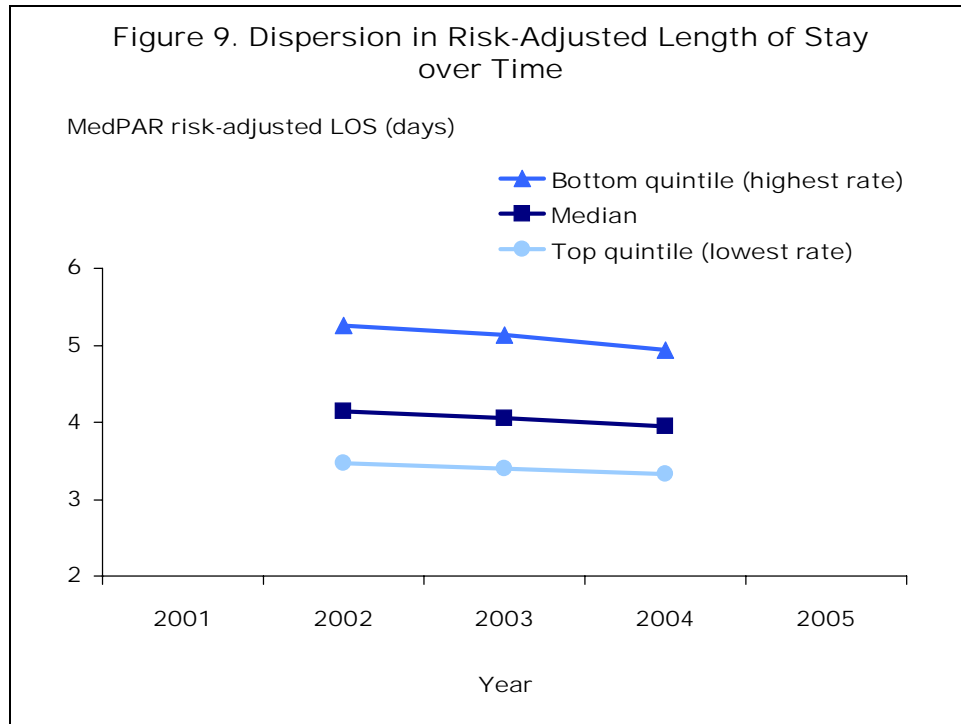


Figure 8. Dispersion in Risk-Adjusted Morbidity Rates over Time





### **100 Most-Improving and 100 Most-Deteriorating Hospitals in Quality and Efficiency Measures**

As noted above, how much a hospital’s performance in quality and efficiency has changed can be measured by the difference in the quality and efficiency index between the starting and the ending year. In both public data sets, the 100 most-improving and 100 most-deteriorating hospitals showed the following characteristics:

- Hospitals showing the greatest jumps in quality most often began at the very lowest end of the quality spectrum (suggesting they jumped because they had the most room to improve); conversely, hospitals showing greatest deterioration most often began at the top-performing level (suggesting they had the most room to fall). In summary, in addition to a general improvement in performance over time, there appears to be temporal regression toward the mean (Figures 10 and 11).
- Most-improving hospitals in quality tend to be smaller than average size, and are less likely than other hospitals to be major teaching institutions (Figures 12 and 13).
- Most-deteriorating hospitals in quality tend to be smaller than average size and show mixed results on teaching status (Figures 12 and 13).
- Most-improving hospitals in terms of efficiency tend to be smaller than average size, and are more likely to be major teaching institutions (Figures 12 and 13).
- Most-deteriorating hospitals in efficiency are mixed with respect to size and are less likely to be major teaching institutions (Figures 12 and 13).



- Geographically, based on the MedPAR data, New York State was disproportionately represented among the group of 100 most-improving hospitals for both quality and efficiency, as was Alabama to a lesser extent. In addition, Tennessee had a disproportionate number of hospitals among the top quality improvers (only) and New Jersey had a notably high proportion of the top efficiency improvers (only). Among the states that were consistently highly represented in the most-deteriorating group of hospitals for both quality and efficiency were Arizona, California, and South Carolina as well as the territory of Puerto Rico. In addition, Minnesota was somewhat highly represented in the most-deteriorating group for efficiency (only). The distribution of the top 100 and bottom 100 hospitals for quality and efficiency across the United States is detailed in the [Appendix](#).

**Graphic Illustrations of Characteristics of Most-Improving and Most-Deteriorating Hospitals**

Figure 10 illustrates the finding that most-improving hospitals for both quality and efficiency tend to start at relatively low levels of performance.

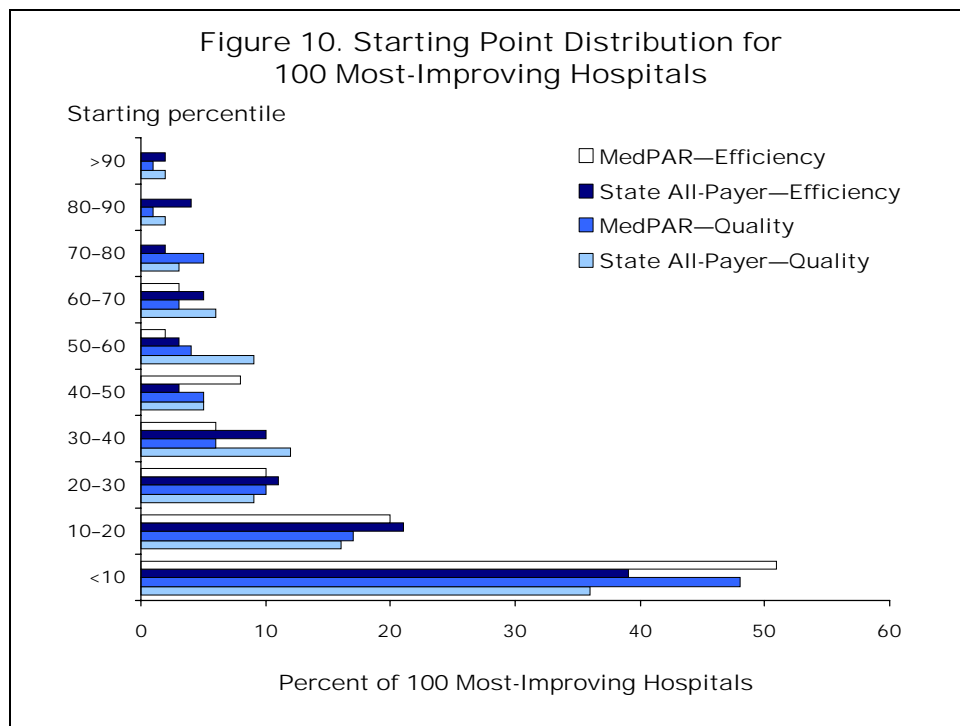


Figure 11 illustrates the finding that the most-deteriorating hospitals for both quality and efficiency tend to begin at high levels of performance.

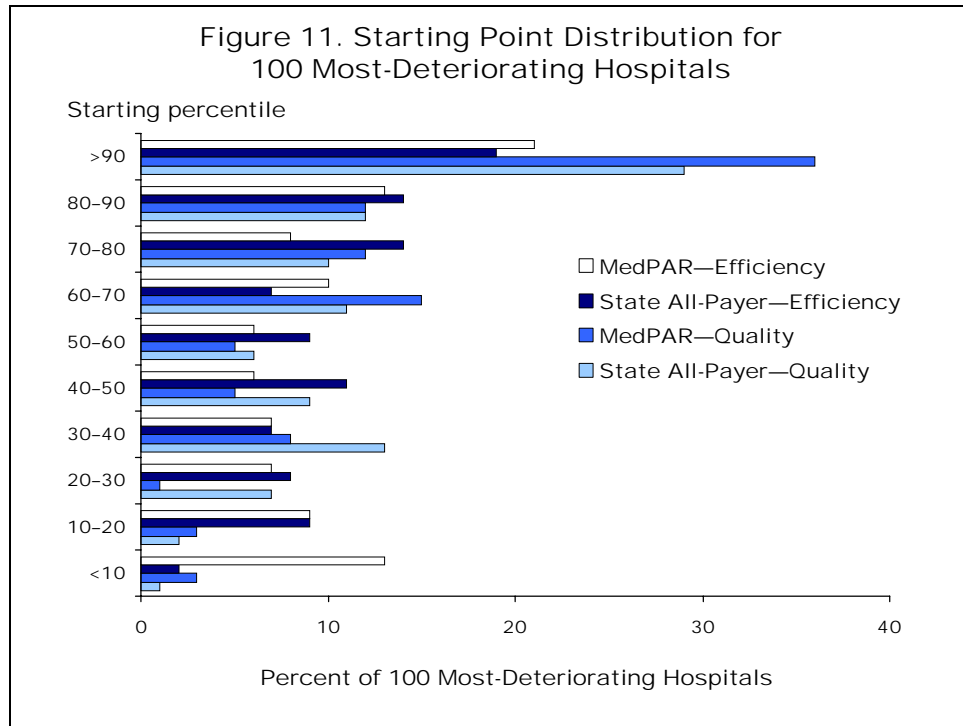


Figure 12 illustrates the finding that the 100 most-improving hospitals in quality and 100 most-improving hospitals in efficiency tend to be smaller than average size (in terms of discharges per year). The 100 most-deteriorating hospitals in quality also tended to be smaller than average, while the results were mixed for the most-deteriorating hospitals in efficiency.

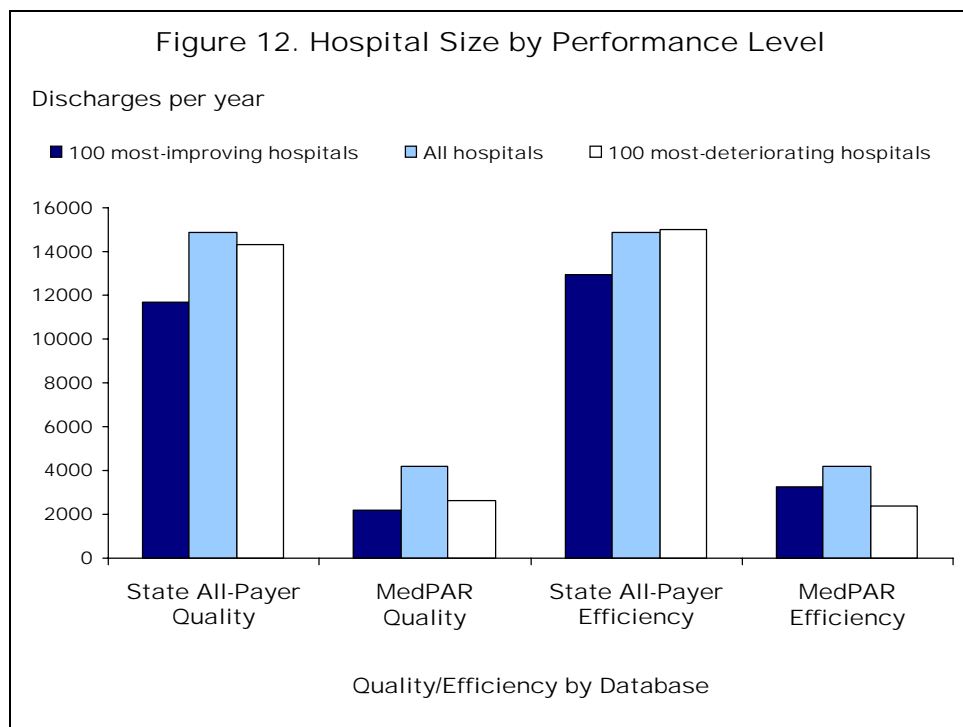
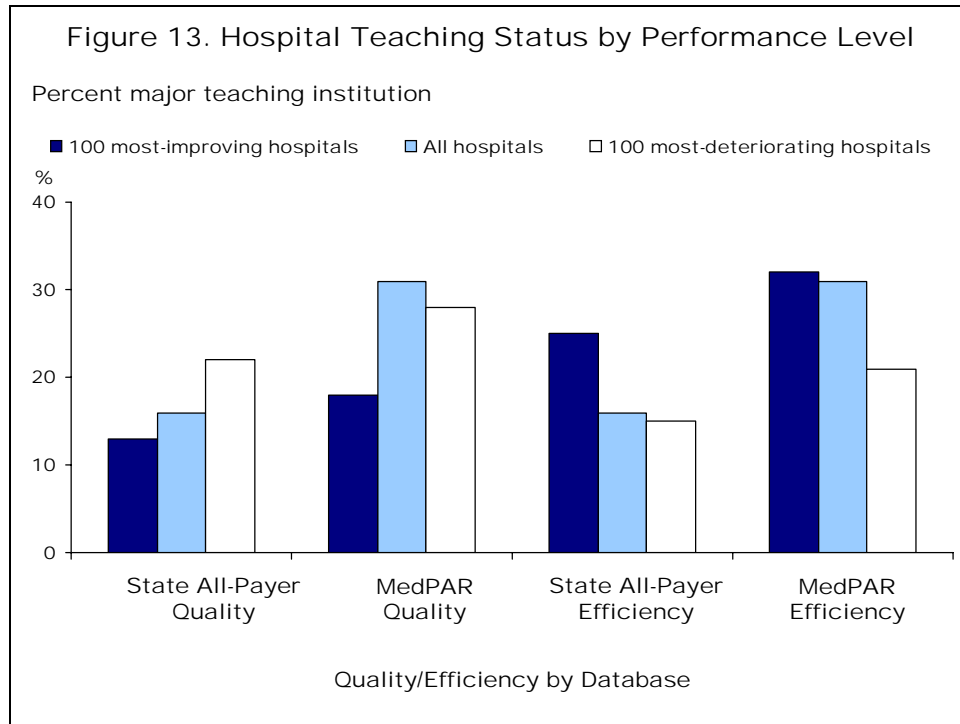


Figure 13 illustrates the finding that major teaching institutions are underrepresented among the most-improving hospitals in quality and the most-deteriorating hospitals in efficiency. Teaching institutions are overrepresented among most-improving hospitals in efficiency.

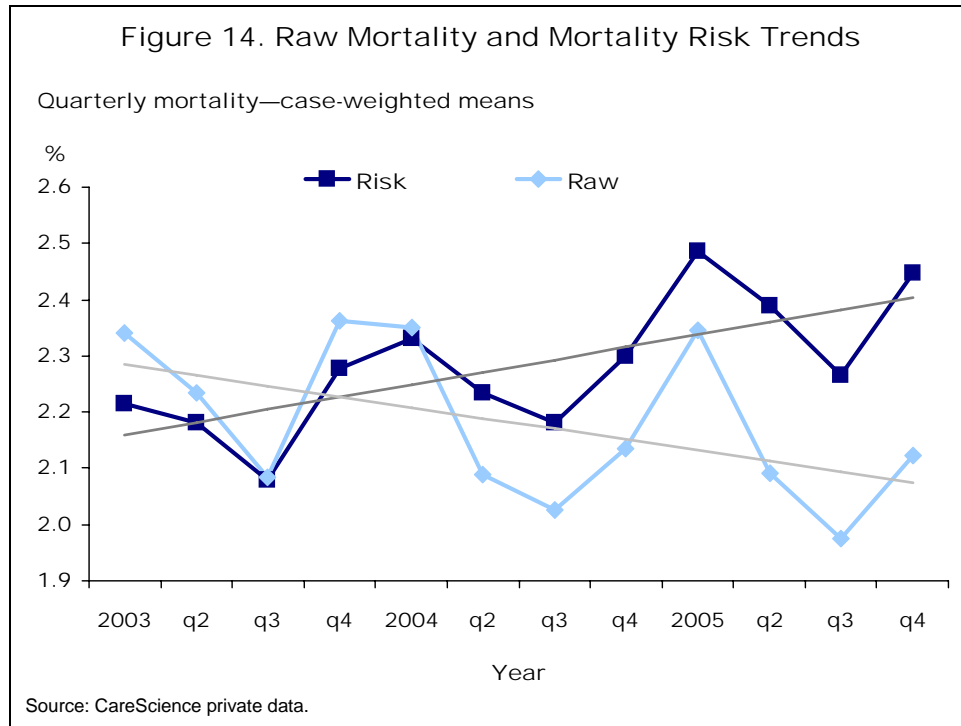


## DISCUSSION

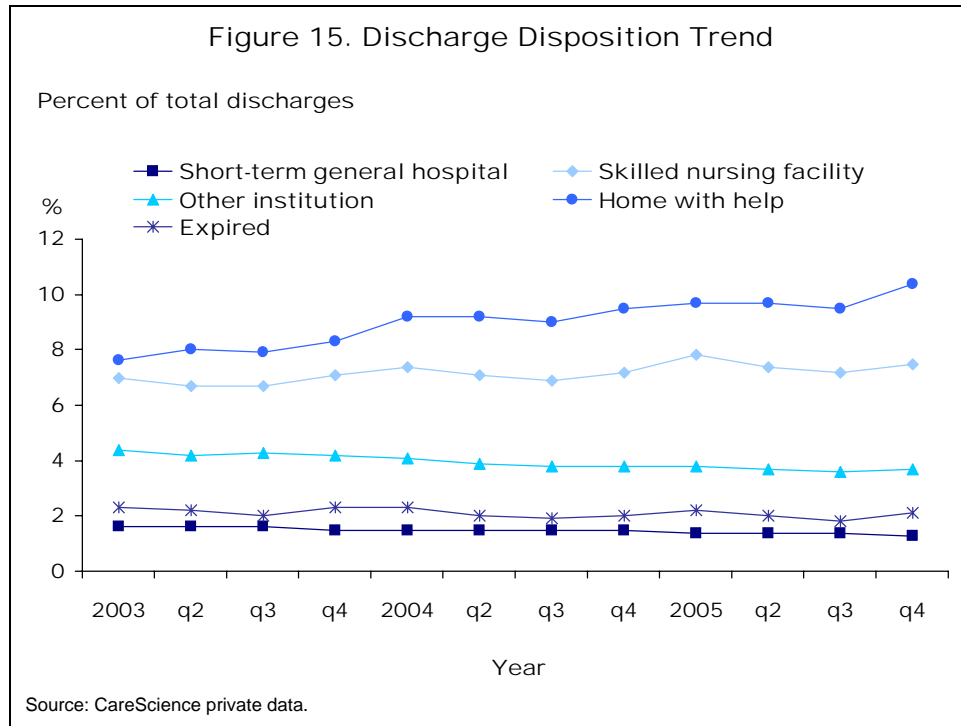
There are clearly some caveats in identifying hospital performance trends and interpreting them, generally related to the realities of how hospital records are kept and what appears in the electronic record, most of which come from chart face sheets and uniform billing forms. For example, subtle differences in scoring can make a large difference in ranking, especially among hospitals that cluster together near the median of the bell-shaped distribution. It is easier to identify with confidence hospitals at the tail ends—those most improving or most deteriorating. Indeed, the hospitals selected for case study analysis in the companion report were among the 100 most-improving (out of nearly 3,000) hospitals.

### Falling Actual Mortality Rate and Rising Mortality Risk

The impressive decline in risk-adjusted mortality over three years and across all three data sets is a combination of both falling raw mortality rates and rising mortality risks, as illustrated in Figure 14. The CareScience private data suggest that falling raw mortality rates and rising mortality risks each contributed equally to the phenomenon of significant decline (improvement) in risk-adjusted mortality rates. Falling raw mortality rates have no

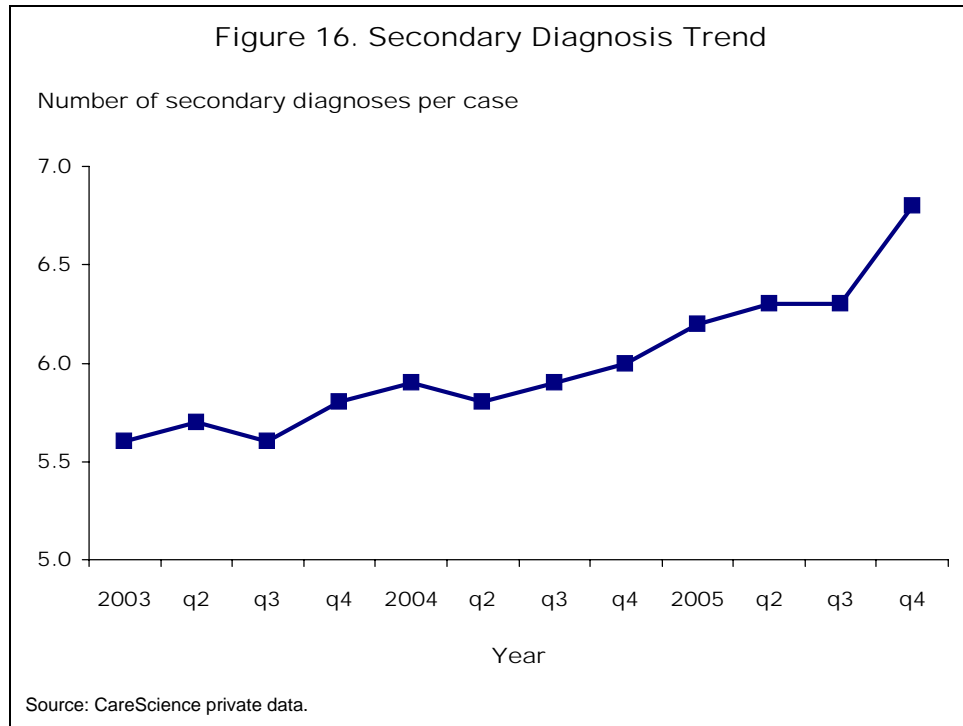


doubt resulted from real improvements in care, such as better diagnostic techniques, earlier interventions, better treatments, more effective rescuing efforts, and other initiatives. But other factors may be at play as well. For example, hospital discharge policy may also influence the measured raw mortality rate, without truly saving lives. For instance, transferring patients to other hospitals or discharging moribund patients to other facilities helps reduce a hospital’s measured inpatient mortality rate. CareScience private data show a distinct upward trend in the proportion of patients who were discharged to their homes with medical help (up 21%) and to skilled nursing facilities, with a concomitant decline in the proportion of patients who were discharged directly to self care/home (Figure 15). Although not directly measured in this study, some of this trend may be related to hospitals taking advantage of hospice care instead of letting patients die in acute-care settings. Whatever the motivation, there is no doubt that discharge policy has a direct effect on the measured raw mortality rate.



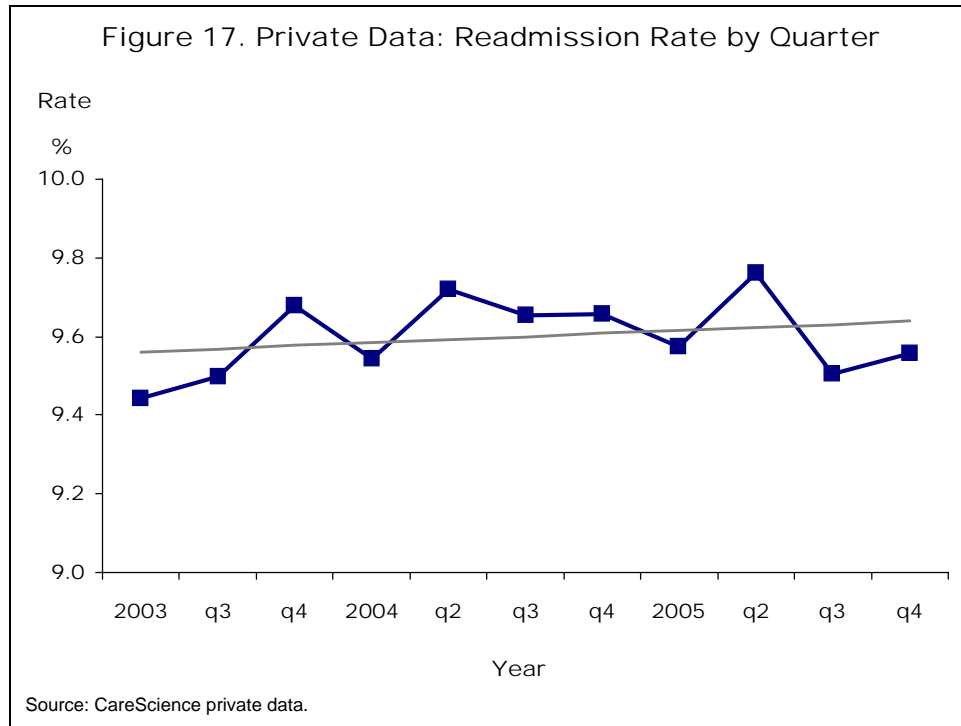
Over the study time period there has been a general increase in inpatient acuity. Hence, the risk of mortality has actually been rising. Factors such as the aging population and rising prevalence of chronic conditions, including the marked increase in type 2 diabetes, underlie the trend. In addition, the growing trend to deliver minor surgery on an outpatient basis has resulted in a decline in the proportion of low-risk inpatients, selectively leaving hospital beds occupied by ever more complicated and severely ill patients.

It equally might be true that at least some of the perceived increase in acuity may well result from hospitals coding patient conditions more consciously and completely. By making sure that its measured patient acuity is as high as possible, a hospital can lower its risk-adjusted mortality rate. Increased scrutiny by payers and regulators has increased the incentive to project such higher quality in the recent past. Figure 16 shows that the number of secondary diagnoses reported per case increased by more than 20 percent over the three-year study period for hospitals in the CareScience private data set. Limitations to the information available for this study make it very difficult to allocate the general rise in mortality risk between actual population trends and perceptions due only to systematic changes in documentation and coding practices among hospitals. Nonetheless, in the face of an apparent increase in acuity, there have been declines in both risk-adjusted mortality and raw mortality, suggesting that in-hospital mortality has truly been improving over the study period.



### **Length of Stay and Readmission**

For some time now inpatient lengths of stay have been getting shorter. This study confirms the trend in all three data sets. Because length of stay is highly correlated with hospitals' expenditure on each patient, the declining trend can be viewed as a response to the increasing financial pressures. In some cases, new technologies enable early discharge without negative medical consequences. In other cases, early discharge might result in readmission. One supposition is that recent changes in hospital discharge policies aimed at reducing lengths of stay have contributed to a general rise in readmission rates. Analysis of the CareScience private database does not support that speculation; according to these data, readmission rates have been stable over the past three years, although this finding is based on a relatively small number of hospitals (Figure 17).<sup>9</sup>



### Implications for Further Study

The limitations of this study (described in this section and the [Appendix](#)) and some of the results suggest that further research is warranted to shed greater light on the true trends in hospital performance. For example, additional research is needed to tease out how much of the change in mortality is due to coding (e.g., including more diagnoses and comorbidities), how much is related to discharging patients earlier (either appropriately or inappropriately), and how much is due to actual improvement in care. Also, it would be helpful to better understand what lies behind the seemingly opposing trends in morbidity and complication rates for each database, as well as differences between the CareScience private database and the two public databases.

The relatively short (three-year) time frame in this study suggests that, as more data become available, the research could be updated and extended, with a particular focus on Select Practice hospitals and/or “high improvers.” Such research would shed further light on sustained change in hospitals.

The changes seen in discharge patterns suggest that it would be worthwhile to examine patient preferences regarding alternative discharge settings (e.g., hospice, acute care, home), as well as costs and levels of patient satisfaction at these various settings. For example, further documentation of greater patient/family satisfaction along with lower

costs related to end-of-life care in hospice and/or home settings (versus acute care settings) could have important implications for discharge policies and national health expenditures.

Additional research could examine the possible influence of public and private sector policies that may have been catalysts for performance changes during the study years. It could help identify specific policies or market conditions that may have played a role in states in which hospitals exhibited disproportionate improvement or deterioration. Finally, while we observed commonalities in the quality improvement change process across the four case study hospitals (selected from among the 100 top improvers in quality), a qualitative analysis of a larger number of highly improving hospitals, as well as top-performing hospitals, could help confirm our findings and our ability to generalize to other hospitals and institutions. Clearly, the goal of this research should be to provide tools and strategies to help the low-performing hospitals raise their performance, and to create a tighter distribution of hospitals around the high-performance end of the spectrum.



## APPENDIX. METHODOLOGICAL DETAILS

### DATA SETS

Three types of data are used in this study. Each has its own advantages and disadvantages. First, the Medicare inpatient data sets (MedPAR) are made available from the Centers for Medicare and Medicaid Services (CMS). It covers all Medicare beneficiaries nationwide, predominantly patients over 65 years old, and does not cover certain common medical services, such as obstetrics and pediatrics. Each annual data set includes about 12 million patient records from about 6,000 hospitals. As the population has aged, the number of patient records has been growing faster than the general population. MedPAR data become available with a lag somewhat in excess of one year. For this study, the most recent three-year data span the years 2002, 2003, and 2004.

The second data set used is State All-Payer. Some states provide all-payer data through their hospital associations or public agencies. They include discharges from virtually all payer classes and cover patients of all ages. Comprehensive all-payer state data are available from fewer than 20 states, most of which are located along the Atlantic and Pacific coasts. Moreover, the lag time on these data sets is almost two years. The most recent available state data span the years 2001, 2002, and 2003. They contain more than 20 million records from over 2,000 hospitals in each year. Since the standards of hospital care are in constant flux (reflected in part by new codes appearing every year in order to reflect changes in diagnosis, procedure, diagnosis-related group, etc.), the longer time lag makes the data less relevant to the current situation. Still, state data remain a good source for hospital comparisons because of their volume and completeness across disease and treatment groupings.

For this project some states were removed because their data were not available for all three years. The final database for this study includes the following states: AZ, CA, FL, MA, MD, NJ, NY, PA, TX, VA, WA, and WI. Even within these states, some hospitals had to be removed because their facility type was unknown and their Medicare-ID designation could not be determined. The last three digits of the Medicare ID, indicating facility type, are used to ensure that only acute-care facilities are included in this study. Further, in order to achieve an acceptable level of statistical reliability, the public data were filtered to exclude the smallest hospitals, specifically the ones whose discharges per year were in the lowest 25th percentile, where the cutoff is 265 discharges per year in MedPAR and 1,500 discharges per year in the all-payer state database. At the data processing step, the smallest hospitals have been removed. Since smaller hospitals give very noisy quality and efficiency signals, the threshold of volume requirement for the final

reports rises to the median point, where the cutoff is 850 discharges per year in MedPAR and 5,000 discharges per year in the all-payer state database. In addition, any hospital that is not represented in all three years of the study is removed from the final reports. Taking all of these filtering requirements together resulted in a total of 2,943 hospitals (in all states) from the MedPAR file and 1,090 hospitals (in 12 states) from the all-payer state database.

In addition to the MedPAR and state all-payer data, this study made extensive use of a third set composed of CareScience’s private data. Because the CareScience private data are collected in compliance with its “Master Data Specification,” data elements can be held to the highest standards for completeness, quality, and consistency. Because the private data contain more detailed elements than public data, including resource usage and treatment timing, more sophisticated modeling techniques could be applied. Another advantage of the private data is their timeliness. For this study inpatient data span the years 2003, 2004, and 2005. They contain about 2.5 million records per year from 149 acute-care hospitals.

## **RISK ADJUSTMENT METHODOLOGY**

The purpose of the risk-assessment model is to generate expected or “standard” outcomes under typical care based on a patient’s health status and other relevant patient characteristics. Patient-level risks for a variety of target outcomes are assessed via a stratified multiple regression model. Overall, the model has the following function form:

$$y_{ijkl} = x_{ijkl} \beta_{kl} + \varepsilon_{ijkl}, \forall ijkl$$

where  $y_{ijkl}$  is the value for each outcome,  $l$ , at the patient level,  $i$ , for each provider,  $j$ , and principal diagnosis  $k$ ;  $x_{ijkl}$  is a vector of patient characteristics and socioeconomic factors;  $\beta_{kl}$  is the marginal effect of the independent variables on the outcome measure; and  $\varepsilon_{ijkl}$  is the random error component of the model. The strata ( $k$ ) are roughly based on three-digit level ICD-9-CM diagnosis codes. Rare and insignificant diagnoses are rolled up into broad diagnosis groups (BDGs), which are defined in the ICD-9-CM book.

The vector of patient characteristics (set of regressors or independent variables) includes clinical factors (principal diagnosis, chronic disease, urgency of admission, comorbidity severity score, defining procedure proxy, and some special population specific indicators), demographic factors (age, sex, race, and income class), and selection factors (travel distance, payer class, and admission source).

Expected outcomes (outcome risks) are generated at the patient level for each of four outcomes: mortality, complications, major morbidity, and length of stay. The patient's risk score is the outcome expected for that patient under standard or typical care, given the patient's health status and other relevant characteristics. These individual risk scores can be aggregated to provide measures of quality and efficiency of hospital services that can be compared across hospitals. Moreover, these comparisons can be constructed for any well-defined population, for example one identified by service line or attending physician. If the average raw value is less than the average risk, the service line or physician is performing above the benchmark.

The risk-adjusted outcome for each hospital is calculated as the sum of overall outcome mean and the individual hospital's outcome deviation (raw – risk). The overall outcome mean is constant so that the deviation determines the hospital's performance level, relative to other hospitals.

## **PERFORMANCE MEASUREMENT**

Based on prior research for the Corporate Hospital Rating Project, risk-adjusted adverse outcome rates for mortality, morbidity, and complications are combined into a single quality measure whose function is  $Q_h = 0.46(T_h)^{0.96} + 0.29(B_h)^{0.91} + 0.25(C_h)^{0.94}$ , where Q, T, B, C and h represent quality index, risk-adjusted mortality, risk-adjusted major morbidity, risk-adjusted complications, and facility, respectively. The quality index (Q) was then inverted and normalized with 100 as the mean. Greater values of Q indicate better quality. Hospitals then are ranked according to their quality index.

Length of stay is used as a proxy for efficient resource usage, based on the assumption that a hospital spends more resources on patients who stay longer in the hospital for a given disease. Since length of stay is well defined and unambiguous for each patient, it is a reliable measure for a patient-level model. (By contrast, the measure of "costs" suffers from a number of vagaries related to differences in accounting conventions and the loose relationship between billing and reimbursement to say nothing of true treatment costs. These ambiguities often make it very difficult to make meaningful comparisons of cost across institutions.)

Hospital performance along the efficiency dimension is measured as the ratio between the actual length of stay and the expected length of stay. After inversion and normalization, the ratio becomes an efficiency index with 100 as the mean. Greater values indicate higher efficiency.

A hospital's quality and efficiency scores determine its position in the Select Practice grid. In this study, each hospital's performance is measured over a three-year time span. The hospital's scores in each year put it at one point in the Select Practice grid in each year. Over time, the hospital's position can move along both the quality and efficiency dimensions. The relationships among the three points (direction and the distance in the grid) give a picture of hospital performance over the three years.

On each dimension, the direction and difference between the starting and ending point indicate whether and how much a hospital's performance has improved or declined. Hospitals are then ranked according to the difference on either quality or efficiency dimension. In order to characterize the most-improving and most-deteriorating hospitals, the top and bottom 100 hospitals are identified according to the ranks.

The quality index is composed of three adverse outcomes: mortality, complication, and morbidity. For individual outcomes, the three-year trend in any risk-adjusted outcome is classified into three categories: decreasing, flat, and increasing. To be classified as "decreasing," the risk-adjusted outcome in the final year must be statistically significantly lower than in the initial year at the 95 percent confidence level. Similarly, to be classified as "increasing," the risk-adjusted outcome in the final year must be statistically significantly higher than in the initial year at the 95 percent confidence level. "Flat" means no statistically significant change.

A hospital is put into its respective performance category based on the time change in its risk-adjusted outcomes between the first and last years of the three-year time span and the associated standard error. Because they are adverse outcomes, a lower risk-adjusted rate means better performance. If the difference (last year minus first year) is greater than two standard errors, the outcome is considered to be increasing, hence a deterioration in performance. If the difference is less than the negative of two standard errors, the outcome is considered as decreasing, meaning a performance improvement. Within the cutoffs, the outcome is considered to be no significant change (flat).

In each category, the time trend is noted as either steady or non-monotonic, i.e., either up-down ("A" shaped) or down-up ("V" shaped). The pattern is determined by the difference and standard error of the middle year, relative to the first and last years. If the middle year value is more than two standard errors above both the first and last year (above the 95 percent confidence interval of both endpoints), the pattern is labeled "up-down." If the middle year value is more than two standard errors below both the first and last year (below the 95 percent confidence interval of both endpoints), the pattern is labeled "down-up." Otherwise the pattern is labeled "steady."

## DETAILED TABULATIONS OF FINDINGS

### Detailed Tabulations of Mortality, Complications, and Morbidity Trends

Note: The “unknown” pattern refers to cases where one of the data points was missing.

Table A-1. Mortality Trend Across Three Data Sets

<b>Hospital Database</b>		<b>State All-Payer n=1090</b>	<b>MedPAR n=2943</b>	<b>CareScience Private Group n=149</b>
Time period		2001–2003	2002–2004	2003–2005
<b>Category</b>	<b>Pattern</b>			
Improve	Steady	40.2%	37.1%	53.0%
Improve	Up–Down	0.8%	0.4%	0.0%
Improve	Down–Up	0.5%	0.2%	1.3%
Improve	Unknown	0.0%	0.0%	1.3%
<i>Subtotal</i>		<i>41.5%</i>	<i>37.7%</i>	<i>55.7%</i>
Flat	Steady	35.0%	41.3%	24.8%
Flat	Up–Down	10.9%	7.8%	4.7%
Flat	Down–Up	5.2%	8.3%	2.7%
Flat	Unknown	0.0%	0.0%	8.7%
<i>Subtotal</i>		<i>51.2%</i>	<i>57.4%</i>	<i>40.9%</i>
Deteriorate	Steady	6.9%	4.7%	3.4%
Deteriorate	Up–Down	0.4%	0.0%	0.0%
Deteriorate	Down–Up	0.1%	0.1%	0.0%
Deteriorate	Unknown	0.0%	0.0%	0.0%
<i>Subtotal</i>		<i>7.3%</i>	<i>4.9%</i>	<i>3.4%</i>

Table A-2. Complication Trend Across Three Data Sets

Hospital Database		State All-Payer n=1090	MedPAR n=2943	CareScience Private Group n=149
Time period		2001–2003	2002–2004	2003–2005
<b>Category</b>	<b>Pattern</b>			
Improve	Steady	34.5%	37.3%	16.8%
Improve	Up–Down	0.6%	1.4%	0.0%
Improve	Down–Up	4.4%	1.4%	2.7%
Improve	Unknown	0.0%	0.0%	2.7%
<i>Subtotal</i>		<i>39.4%</i>	<i>40.1%</i>	<i>22.1%</i>
Flat	Steady	11.8%	19.5%	14.8%
Flat	Up–Down	5.4%	9.3%	0.7%
Flat	Down–Up	12.1%	8.0%	14.8%
Flat	Unknown	0.0%	0.0%	5.4%
<i>Subtotal</i>		<i>29.4%</i>	<i>36.8%</i>	<i>35.6%</i>
Deteriorate	Steady	27.3%	20.2%	35.6%
Deteriorate	Up–Down	1.4%	1.8%	0.7%
Deteriorate	Down–Up	2.5%	1.1%	4.0%
Deteriorate	Unknown	0.0%	0.0%	2.0%
<i>Subtotal</i>		<i>31.2%</i>	<i>23.0%</i>	<i>42.3%</i>

Table A-3. Morbidity Trend Across Three Data Sets

<b>Hospital Database</b>		<b>State All-Payer n=1090</b>	<b>MedPAR n=2943</b>	<b>CareScience Private Group n=149</b>
Time Period		2001–2003	2002–2004	2003–2005
<b>Category</b>	<b>Pattern</b>			
Improve	Steady	5.5%	10.3%	42.3%
Improve	Up–Down	0.1%	0.6%	0.7%
Improve	Down–Up	0.5%	0.1%	1.3%
Improve	Unknown	0.0%	0.0%	2.7%
<i>Subtotal</i>		<i>6.1%</i>	<i>11.1%</i>	<i>47.0%</i>
Flat	Steady	17.2%	29.1%	22.8%
Flat	Up–Down	8.1%	14.4%	4.0%
Flat	Down–Up	4.2%	3.7%	9.4%
Flat	Unknown	0.0%	0.0%	6.7%
<i>Subtotal</i>		<i>29.4%</i>	<i>47.2%</i>	<i>43.0%</i>
Deteriorate	Steady	60.6%	38.9%	8.7%
Deteriorate	Up–Down	3.1%	2.5%	0.0%
Deteriorate	Down–Up	0.7%	0.3%	0.7%
Deteriorate	Unknown	0.0%	0.0%	0.7%
<i>Subtotal</i>		<i>64.5%</i>	<i>41.7%</i>	<i>10.1%</i>

Table A-4. Length of Stay Trend Across Three Data Sets

<b>Hospital Database</b>		<b>State All-Payer n=1090</b>	<b>MedPAR n=2943</b>	<b>CareScience Private Group n=149</b>
Time period		2001–2003	2002–2004	2003–2005
<b>Category</b>	<b>Pattern</b>			
Improve	Steady	55.0%	62.4%	55.0%
Improve	Up–Down	4.1%	2.7%	4.0%
Improve	Down–Up	3.9%	1.7%	5.4%
Improve	Unknown	0.0%	0.0%	4.0%
<i>Subtotal</i>		<i>62.9%</i>	<i>66.8%</i>	<i>68.5%</i>
Flat	Steady	5.7%	11.1%	4.7%
Flat	Up–Down	6.6%	6.5%	2.7%
Flat	Down–Up	4.3%	5.4%	3.4%
Flat	Unknown	0.0%	0.0%	4.0%
<i>Subtotal</i>		<i>16.6%</i>	<i>23.0%</i>	<i>14.8%</i>
Deteriorate	Steady	16.6%	8.9%	13.4%
Deteriorate	Up–Down	1.9%	0.6%	0.7%
Deteriorate	Down–Up	1.9%	0.6%	0.7%
Deteriorate	Unknown	0.0%	0.0%	2.0%
<i>Subtotal</i>		<i>20.5%</i>	<i>10.2%</i>	<i>16.8%</i>



Table A-5 illustrates hospital quality and efficiency trends by state. Highlighted states are those that have a disproportionate number of hospitals among the 100 most-improving (dark shading) or 100 most-deteriorating (light shading) hospitals, based on MedPAR data for the 2002–2004 period.

Table A-5. Hospital Quality and Efficiency Trends by State  
Distribution of Top/Bottom 100 hospitals Based on Improvement

State	All Hospitals			Quality		Efficiency	
	Count	Percent	Expected	Top 100	Bottom 100	Top 100	Bottom 100
AK	4	0.1%	0.1				
<b>AL</b>	74	2.5%	2.5	<b>6</b>	2	<b>6</b>	4
AR	47	1.6%	1.6	3	2	4	1
<b>AZ</b>	42	1.4%	1.4		<b>5</b>		<b>4</b>
<b>CA</b>	261	8.9%	8.9	6	<b>13</b>	7	<b>17</b>
CO	30	1.0%	1.0		2		
CT	30	1.0%	1.0		2		
DC	7	0.2%	0.2			1	
DE	5	0.2%	0.2				2
FL	158	5.4%	5.4	5	4	1	7
GA	86	2.9%	2.9	4	2	3	3
HI	11	0.4%	0.4		2	2	
IA	32	1.1%	1.1		1		1
ID	11	0.4%	0.4				
IL	131	4.5%	4.5	4	1	3	2
IN	70	2.4%	2.4	2	4	2	1
KS	36	1.2%	1.2			1	
KY	61	2.1%	2.1	5		4	4
LA	66	2.2%	2.2	2	2	2	4
MA	58	2.0%	2.0		2		
MD	45	1.5%	1.5	1	3	1	
ME	24	0.8%	0.8	1	2		1
MI	93	3.2%	3.2	1	2	3	1
<b>MN</b>	49	1.7%	1.7		3	1	<b>5</b>
MO	73	2.5%	2.5	3	3		3
MS	51	1.7%	1.7	2	3	4	1
MT	10	0.3%	0.3			1	
NC	89	3.0%	3.0	5		2	4
ND	8	0.3%	0.3				
NE	16	0.5%	0.5	1			1

State	All Hospitals			Quality		Efficiency	
	Count	Percent	Expected	Top 100	Bottom 100	Top 100	Bottom 100
NH	15	0.5%	0.5	1	2		
<b>NJ</b>	75	2.5%	2.5	3	1	<b>10</b>	1
NM	18	0.6%	0.6	2	1	2	1
NV	13	0.4%	0.4				1
<b>NY</b>	174	5.9%	5.9	<b>10</b>	4	<b>22</b>	5
OH	124	4.2%	4.2	6	2	3	3
OK	46	1.6%	1.6		2	1	
OR	25	0.8%	0.8				
PA	151	5.1%	5.1	6	4	1	1
<b>PR</b>	40	1.4%	1.4	1	<b>5</b>		<b>9</b>
RI	10	0.3%	0.3				
<b>SC</b>	44	1.5%	1.5		<b>4</b>		<b>5</b>
SD	9	0.3%	0.3		1		
<b>TN</b>	79	2.7%	2.7	<b>8</b>	1	4	4
TX	200	6.8%	6.8	7	3	4	2
UT	17	0.6%	0.6				
VA	70	2.4%	2.4	1	4	3	1
VT	7	0.2%	0.2				1
WA	45	1.5%	1.5		2		
WI	64	2.2%	2.2	2	3	1	
WV	35	1.2%	1.2	1	1	1	
WY	4	0.1%	0.1	1			
<b>Total</b>	<b>2943</b>	<b>100%</b>	<b>100</b>	<b>100</b>	<b>100</b>	<b>100</b>	<b>100</b>
Chi-squared independence test (p-values)				0.046	0.026	0.000	0.000

## DIVERGENCE IN COMPLICATION AND MORBIDITY TRENDS ACROSS DATA SETS

As noted above, trends indicate that mortality, especially risk-adjusted mortality, has been uniformly declining across data sets, whereas complications and morbidity show mixed results. Declines in complications together with increases in morbidity dominate the public data, while the reverse is true in CareScience private data. The following factors may help to explain the divergence in complication trends and morbidity trends across the data sets:

1. The three data sets do not cover the same time range.
2. In the public data sets the recorded number of secondary diagnoses per patient is restricted to no more than eight. No such maximum restricts the CareScience

private data, where all documented secondary diagnoses are present in the data. As a consequence, both the imputed complications rate and the rate of comorbidities have increased faster in the CareScience data than in the public data. The differential effect (on CareScience vs. public data) on measured total complications is greater than the effect on morbid (severe) complications, because the latter are more likely to be tracked in both types of data. Hence, the overall effect is that CareScience data relative to public data show a greater increase in measured risk-adjusted complications (measured complication rate relative to expected complication rate), as well as a greater decline in measured risk-adjusted major morbidity (measured morbidity relative to expected morbidity). In summary the greater number of reported secondary diagnoses in the CareScience data raise the simple complication rate as well as the complication morbidity risk of patients, both of which help to *raise* the risk-adjusted complication rate and to *lower* the risk-adjusted morbidity rate.

3. The risk model specifications differ somewhat across the three data sets, largely because of differences in patient data elements. Because the private data set has more data fields than the public data sets, the risk model for the private data set is richer and has more explanatory power. For example, certain “rescuing” procedures can drive up morbidity risk. Depending on the timing, these rescues may indicate patient’s conditions upon admission, or deterioration after treatment. The CareScience analytic model allows higher-risk scores only when these interventions occurred within a certain time interval after admission. In the public data sets, the timing information is not available, requiring this particular risk adjustment to fall from the risk estimation. The end result is relative diminution of morbidity risk in public data sets, hence rising risk-adjusted morbidity.

### **FALLING RISK-ADJUSTED MORTALITY IN THE FACE OF RISING RISK-ADJUSTED MORBIDITY**

One would expect that higher morbidity (seen in the two public data sets) should presage higher, not lower, mortality. The lower mortality in the face of higher morbidity may be due to hospitals generally improving their success in rescuing failing patients. Another possible explanation is that rising morbidity may be due to trends toward more complete documentation, although this is not consistent with the downward trend in complications. Additional research might shed light on these findings.

## NOTES

<sup>1</sup> Committee on Quality of Health Care in America, Institute of Medicine, *To Err Is Human: Building a Safer Health System* (Washington, D.C.: National Academies Press, 2000); and Committee on Quality of Health Care in America, Institute of Medicine, *Crossing the Quality Chasm: A New Health System for the 21st Century* (Washington, D.C.: National Academies Press, 2001).

<sup>2</sup> CareScience provides care management and clinical access solutions for health care providers; it develops and implements clinical technology designed to reduce complications and medical errors, optimize patient flow, identify causes of problematic outcomes, and enable the secure exchange of clinical information within an enterprise or across a community. For more information see <http://www.carescience.com/>.

<sup>3</sup> For a more detailed discussion of the rationale and development of these measures, see D. J. Brailer, E. A. Kroch, M. V. Pauly et al., “Comorbidity-Adjusted Complication Risk: A New Outcome Quality Measure,” *Medical Care*, May 1996 34(5):490–505.

<sup>4</sup> Most-deteriorating hospitals in quality also tend to be smaller than average size, likely reflecting greater volatility in institutions with fewer patients.

<sup>5</sup> Sharon Silow-Carroll, Tanya Alteras, and Jack A. Meyer, [\*Hospital Quality Improvement: Strategies and Lessons from U.S. Hospitals\*](#) (New York: The Commonwealth Fund, March 2007).

<sup>6</sup> Brailer et al., “Comorbidity-Adjusted,” 1996.

<sup>7</sup> M. V. Pauly, D. J. Brailer, E. A. Kroch et al., “Measuring Hospital Outcomes from a Buyers Perspective,” *American Journal of Medical Quality*, Fall 1996 11(3):112–22.

<sup>8</sup> IOM, *Quality Chasm*, 2001.

<sup>9</sup> Because unique patient identifiers are removed from the public data sets, making it impossible to track patient readmission, we relied on the CareScience private data set to monitor trends in readmission rates. Using the broad definition of readmission (within 30 days, regardless of diagnosis), the quarterly readmission rate is calculated from the private patient-identified data from 149 CareScience acute-care hospitals.

## RELATED PUBLICATIONS

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[\*Hospital Performance Improvement: Are Things Getting Better?\*](#) (April 2007). Ashish K. Jha and Arnold M. Epstein. Commentary

[\*Quality Matters\*](#). Bimonthly newsletter from The Commonwealth Fund.

[\*Paying for Care Episodes and Care Coordination\*](#) (March 2007). Karen Davis. Commentary.

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[\*Journal of Ambulatory Care Management Special Issue: Technology for Patient-Centered, Collaborative Care\*](#) (July–September 2006). Donald Berwick, John H. Wasson, Deborah J. Johnson et al., vol. 29, no. 3 (*In the Literature* summary).

[\*Committed to Safety: Ten Case Studies on Reducing Harm to Patients\*](#) (April 2006). Douglas McCarthy and David Blumenthal.

[\*Nurse Staffing in Hospitals: Is There a Business Case for Quality?\*](#) (January/February 2006). Jack Needleman, Peter I. Buerhaus, Maureen Stewart et al. *Health Affairs*, vol. 25, no. 1 (*In the Literature* summary).

[\*Care in U.S. Hospitals—The Hospital Quality Alliance Program\*](#) (July 21, 2005). Ashish K. Jha, Zhonghe Li, E. John Orav et al., *New England Journal of Medicine*, vol. 353 no. 3 (*In the Literature* summary).

[\*Hospital Quality: Ingredients for Success—Overview and Lessons Learned\*](#) (July 2004). Jack A. Meyer, Sharon Silow-Carroll, Todd Kutyla, et al.

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[\*Hospital Quality: Ingredients for Success—A Case Study of Jefferson Regional Medical Center\*](#) (July 2004). Jack A. Meyer, Sharon Silow-Carroll, Todd Kutyla, et al.

