TEXAS HEALTH AND HUMAN SERVICES COMMISSION

Potentially Preventable Readmissions in the Texas Medicaid Population, Fiscal Year 2009

Public Report

January 2011

Note: **Each hospital can obtain a confidential version of this report, with its own PPR results, through its secure mailbox at www.tmhp.com.**

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Table of Contents

Note: Section 4 is included only in the hospital-specific versions of this report. The public version does not include any confidential hospital-specific information.

TEXAS HEALTH AND HUMAN SERVICES COMMISSION

Readmissions to hospital are expensive, but are often preventable. To enable understanding of this issue, H.B. 1218, 81st Legislature, Regular Session 2009, requires the Health and Human Services Commission (HHSC) to identify potentially preventable readmissions (PPRs) in the Medicaid population and report results confidentially to each hospital. The law also requires each hospital to distribute the information to its care providers.[1]

This report fulfills the legislative requirement to provide PPR information. Each Texas and out-of-state hospital serving Texas Medicaid clients is receiving data on the volume and rate of PPRs in its facility in state fiscal year 2009. A public version of this report is also available. The two reports are identical except that confidential hospital-specific information is excluded from the public report.

This is the first year that PPR analysis has been done. A second analysis, based on SFY 2010 data, will be published in early 2012.

Many people are familiar with Medicare's approach to calculating and reporting readmission rates. HHSC has taken a different approach that is more suitable to the very different needs of the Medicaid population. Our approach considers almost all medical conditions but defines a potentially preventable readmission only when a plausible clinical connection exists between the initial admission and the readmission. A readmission "window" of 15 days is used, and clients in Medicaid fee-for-service (FFS), primary care case management (PCCM), and managed care programs are included. The approach uses PPR software developed by 3M Health Information Systems, and HHSC would like to thank 3M for its extensive assistance.[2] The same approach is used by the Florida Agency for Health Care Administration (and reported at www.floridahealthfinder.gov), the Maryland Health Services Cost Review Commission, and the New York Medicaid program, among other agencies.[3]

Overall, 3.6% of Medicaid inpatients in SFY 2009 had at least one PPR within 15 days of discharge. The cost to Medicaid of these PPRs was $104 million, or about 3.5% of total Medicaid payments to hospitals. Readmissions also create costs for physicians, other providers, and for patients themselves. The PPR rate and the percentage of total payments may seem modest in the context of a very large program. The low overall rate reflects the large volume of obstetric stays, where PPRs are rare (0.8%). For the non-obstetric pediatric population, the PPR rate is 3.9%; for the non-obstetric adult population, the PPR rate is 8.2%. Of clients initially admitted for mental illness or substance abuse, one in ten is readmitted within 15 days, with many having subsequent readmissions. PPR rates are even higher for some individual conditions, ranging up to 19% for major liver diseases.

Not all readmissions are preventable. In calculating PPR rates, the methodology tries to exclude readmissions that were planned or otherwise unavoidable. Even some readmissions that are classified as potentially preventable are, in fact, appropriate. But many readmissions are preventable. Nationwide, readmissions often reflect the absence of excellent care in our health care system, especially in smoothing the transition from the hospital to care in the community or in a post-acute facility. The hospital, with its central role in every community's health-care system, can play a valuable role in improving that transition. The wide variation in casemix-adjusted PPR rates—the hospitals with the highest rates have rates two to four times higher than the hospitals with the lowest rates—suggests that opportunities exist for hospitals to learn from each other. (Casemix refers to the clinical characteristics of the population being served by each individual hospital.) If the number of potentially preventable readmissions were reduced by 10%, the benefits would not only be a savings of more than $10 million to the Medicaid budget but, more importantly, improved health and satisfaction among the clients served by HHSC and the hospitals.

This analysis was performed for HHSC by the Texas Medicaid and Healthcare Partnership (TMHP). Statements and opinions are those of the authors and not necessarily those of the Texas Health and Human Services Commission.

To help hospitals understand this study, and to help us make it more useful to hospitals, TMHP has scheduled in-person presentations in January 2011 in Dallas, Houston, Mission, San Antonio and Amarillo. For details, refer to Question 21 in Section 3 of this document. HHSC is interested in improving methodology and making results more useful to hospitals. At any time, comments and suggestions on this topic are welcomed, and can be emailed to PPR.Report@tmhp.com.

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January 2011

1 Background and Methodology

1.1 Medicaid Payment for Inpatient Hospital Services

In state fiscal year 2009 (September 2008 through August 2009), the Texas Medicaid program paid for 708,541 inpatient stays, representing about 20% of all inpatient stays in Texas. Payments to hospitals totaled $3.3 billion, representing about 8% of the industry's combined inpatient and outpatient revenue.[4]

Medicaid covers clients through three health care delivery methods. Table 1.1.1 shows that 40% of stays are fee-for-service (FFS), meaning that payment is made directly to the hospital by the Medicaid program. Another 29% of stays are considered primary care case management (PCCM). These clients have a designated primary care coordinator, typically a physician, who takes responsibility for coordinating the client's care. The PCCM is not at financial risk for the services that the client receives. Payment for the hospital stay is made directly by the Medicaid program, just as with traditional fee-for-service. The other 32% of stays are for managed care clients. The managed care organization (MCO) accepts financial responsibility for the services received by the client and pays the hospital directly.

In SFY 2009, Medicaid paid for 708,541 inpatient stays, representing about 20% of total inpatient stays statewide.

The table also shows stays and payments by Medicaid Care Category, a categorization intended to reflect the inpatient needs of the Medicaid population as well as the internal organization of a typical hospital. Overall, 36% of Medicaid stays are for obstetrics, 30% for newborns, 16% for clients 17 years of age and younger (excluding newborns and obstetrics) and 18% for non-obstetric adults.

Under all three delivery methods, Medicaid clients 20 years of age and younger can receive an unlimited amount of medically necessary inpatient hospital care. For adults, there are two benefit limits, one at $200,000 in payment per year and the other per spell of illness, which is generally defined as 30 days of inpatient hospital care after an interval of at least 60 days out of the hospital.[5]

Table 1.1.1 Summary of Medicaid Inpatient Hospital Utilization, SFY 2009								
	Stays				Medicaid Payments (in Millions)			
Medicaid Care Category	FFS	PCCM	MCO	Total	FFS	PCCM	MCO	Total
Pediatric								
Respiratory	8,725	11,226	10,293	30,244	$93	$53	$73	$219
Other medical	16,547	17,110	18,534	52,191	$168	$86	$144	$398
Other surgical	5,965	3,541	3,753	13,259	$142	$64	$69	$275
MH/SA	5,881	4,116	6,412	16,409	$38	$21	$33	$91
Subtotal	**37,118**	**35,993**	**38,992**	**112,103**	**$441**	**$223**	**$319**	**$983**
Adult								
Circulatory	8,660	8,910	248	17,818	$65	$58	$2	$126
Other medical	38,403	32,287	2,824	73,514	$217	$153	$15	$385
Other surgical	12,981	8,375	1,153	22,509	$175	$87	$9	$270
MH/SA	4,930	3,775	8,346	17,051	$19	$14	$32	$64
Subtotal	**64,974**	**53,347**	**12,571**	**130,892**	**$476**	**$311**	**$58**	**$845**
Obstetrics	91,551	59,615	100,497	251,663	$217	$130	$254	$601
Newborns	87,870	53,497	70,366	211,733	$300	$153	$334	$787
Ungroupable	696	284	1,170	2,150	$30	$8	$24	$62
Total	**282,209**	**202,736**	**223,596**	**708,541**	**$1,464**	**$826**	**$988**	**$3,278**

Notes

1) FFS=fee for service; PCCM=primary care case management; MCO=managed care organization; MH/SA=mental health/substance abuse

2) Payments exclude payments on Medicare crossover claims and disproportionate share hospital (DSH) payments.

3) Totals in this table may not be identical to other information prepared by HHSC due to differences in service dates, paid dates, dates of analysis, inclusion or exclusion of various claim categories, and other reasons.

1.2 Data Included in the Study

This analysis includes the entire Medicaid population, with three exceptions.

- ***Newborns (under 29 days old)***. The 3M PPR software was not designed for use with this population. Readmissions are rare in the newborn population.

- ***Undocumented aliens.*** Another 83,624 stays were excluded because the patient was an undocumented alien and therefore eligible only for emergency Medicaid. If the patient was discharged and readmitted, the readmission might not be linked to the initial admission.

- ***Dual eligibles.*** Stays for patients who were dually eligible for both Medicare and Medicaid were excluded if Medicare was the primary payer for the stay.[6]

The study includes all Medicaid stays except for newborns, stays for patients with emergency Medicaid, and stays for dual eligibles where Medicare was the primary payer.

A total of 24,307 stays were also excluded from the analysis due to "categorical exclusion" and "non-event" logic in the PPR software, such as stays when patients discharged themselves against medical advice (Section 1.4). As well, the PPR software was configured to search for initial admissions in an 11-month period and readmissions in a 12-month period. This resulted in the exclusion of 30,278 stays that occurred in August 2009.

All results reflect the FFS, PCCM and managed care populations. Hospitals were uniquely identified using their Texas Provider Identifier number (TPI). Because the managed care plans only report the hospital's National Provider Identifier (NPI) to TMHP, each NPI was crosswalked to the appropriate TPI based on data received from the plan such as NPI, provider taxonomy, zip code and type of bill. For 1,388 stays, the NPI could not be crosswalked to an appropriate TPI with a high degree of confidence. These stays were excluded from further analysis.

All data were subject to extensive validation checks, including chaining together multiple claims for a single stay, verifying bill type, examining extreme values of important data fields, and verifying diagnosis and procedure code values. In particular, the accuracy of the PPR software depends on the accuracy of Diagnosis Related Group (DRG) assignment, which in turn depends on the accuracy and completeness of diagnosis and procedure coding. Coding completeness and accuracy were evaluated as described in Section A.2.4 of the appendix. In general, there were no obvious indications of coding problems that would significantly affect the PPR analysis. The exception was that coding by specialty psychiatric hospitals appeared to be noticeably less thorough than at general hospitals that provide similar care. As a result, reported PPR performance may be worse for some psychiatric specialty hospitals than it would be if coding were more complete. Any coding deficiencies in these hospitals would also make reported PPR performance in the general hospitals better than it otherwise would be for mental health and substance abuse treatment, since statewide norms are applied to both groups of hospitals. The magnitude of any discrepancy is unknown but believed to be modest.

Overall, of the 708,541 stays shown in Table 1.1.1, a total of 342,997 stays were excluded from the analytical dataset by design. Another 21,321, or 5.8%, were omitted because of data issues. As a result, the analytical dataset comprised 344,223 stays, each of which was categorized as either an initial admission or as a potentially preventable readmission. Table A.2.1 in the appendix shows a reconciliation of claim counts.

1.3 Potentially Preventable Readmissions as an Indicator of Quality

Readmissions to hospitals have long been recognized as an indicator of quality of care.[7] Many Medicaid programs and other payers have policies under which they may deny payment for specific readmissions that result from sub-standard care in the initial admission. Examples include repeat admissions for asthma or admissions for post-operative bleeding. In principle, denial of payment of these specific cases motivates the hospital to bring its care up to standard.

In recent years, hospitals and payers have taken a different approach to improving quality.[8] Instead of focusing on specific events, and sometimes on specific individuals, the focus is on overall performance. The approach aims for transparency and collaboration between medical providers. Dr. Guy Clifton, a Houston neurosurgeon and health policy analyst, says quality problems "are not about bad people but about good people working in bad systems."[9] The goal of quality improvement is also becoming more ambitious—not just to reduce quality problems, but rather to enable quality successes.

PPR analysis focuses not on individual readmissions but on overall rates, with a goal of encouraging excellent care, especially in the transition from the hospital to the community.

Analysis of hospital-wide PPR rates fit very well with this approach. Even the best systems will have some readmissions. In situations where readmissions are likely included in the plan of care, such as chemotherapy, the PPR software excludes the readmissions entirely. In situations where the readmission is clearly unrelated, the second stay does not count as a PPR. In other situations, for example, pediatric bronchiolitis followed by a similar stay, no attempt is made to identify which specific readmissions could or could not have been prevented. Instead, the hospital-wide rate of PPR is reported and compared with an appropriate norm, with the goal of focusing attention on the entire system of care and the improvement of its outcomes. All such comparisons are adjusted for differences in casemix.

Section 2.3 shows that PPRs need not be directly attributable to poor care. For example, only 2% of PPRs are for post-surgical complications, and even some of those were presumably unpreventable. Much more commonly, readmissions appear to reflect the absence of excellent care, especially in transitioning from inpatient care to care at home or in a post-acute facility. Relatively simple steps can make a real difference. These include scheduling the follow-up appointment before discharge, voice-to-voice transfer of care between the attending physician and the primary care physician, asking the patient to repeat back the discharge instructions, reconciling medication instructions, and placing a follow-up phone call several days after discharge. Overviews of best practices and lessons learned are available from organizations such as the Health Research and Educational Trust, the Institute for Healthcare Improvement, AcademyHealth, and Medicare and Medicaid quality improvement organizations.[10] In Florida, Michigan, New Jersey and elsewhere, hospitals have formed collaboratives to share best practices in reducing readmissions. Within Texas, the Texas Medical Foundation is leading such an effort in Harlingen.

1.4 Defining Potentially Preventable Readmissions

The following is a summary of the PPR methodology developed by 3M Health Information Systems and used for this analysis. No changes were made to the methodology for this analysis. Further detail on the methodology is available in the* Potentially Preventable Readmissions Classification System Definitions Manual, *October 2010 version, available to Texas hospitals by contacting 3M at gmperfetto@mmm.com.

There are many ways to define and report readmissions, with the simplest approach being a count of readmissions for any reason within a given time period. The 3M PPR approach used in this study is more sophisticated in that it includes risk adjustment for severity of illness and counts only readmissions where there was a plausible clinical connection between the reason for the initial admission and the reason for the readmission.

PPRs are identified by comparing the APR-DRG for the initial admission with the APR-DRG for the readmission.

To put this approach into operation, every stay is assigned to an All Patient Refined Diagnosis Related Group (APR-DRG). There are 314 base APR-DRGs, which can be thought of as the reason for admission. Each base APR-DRG has four levels of severity. APR-DRG 139-1, for example, reflects a patient with uncomplicated pneumonia. A patient assigned to APR-DRG 139-2 has both pneumonia and a significant comorbidity such as congestive heart failure. At the extreme, a patient assigned to APR-DRG 139-4 may have pneumonia with multiple organ failure, requiring intensive therapy.

When comparing the reason for admission with the reason for readmission, there are 314 x 314 = 98,596 possible pairs of base APR-DRGs. A 3M panel of clinicians made a judgment about whether each admission/readmission pair represented a potentially preventable readmission. For some pairs, additional factors were considered, including patient age or particular diagnoses and procedures within an APR-DRG. The list of which admission/readmission APR-DRGs are defined as PPRs is available in an appendix to the 3M definitions manual. For each pair that counts as a PPR, the readmission is also

Table 1.4.1
Examples of Clinical Reasons for Potentially Preventable Readmission

Readmission Reason	Readmission DRG Example
Example: Initial admission for APR-DRG 141 -- Asthma	
1 Medical readmission—recurrence	DRG 141 -- Asthma
2A Ambulatory care sensitive condition	DRG 139 -- Pneumonia
2B Readmission—chronic problem	DRG 053 -- Seizure
3 Medical readmission—acute problem	DRG 134 -- Pulmonary embolism
6A Mental health readmission after initial admission not MH/SA	DRG 751 -- Depression
6B Substance abuse readmission after initial admission MH/SA	DRG 775 -- Alcohol abuse
Example: Initial admission for APR-DRG 225 -- Appendectomy	
4 Surgical readmission—recurrence	DRG 221 -- Major bowel proc
5 Surgical readmission—complication	DRG 791 -- OR proc complication
Example: Initial admission for APR-DRG 775 -- Alcohol Abuse	
6C MH/SA readmit after MH/SA admit	DRG 751 -- Depression

Note: APR-DRG=All Patient Refined Diagnosis Related Group; MH/SA=mental health/substance abuse.

Source: 3M Health Information Systems, *Potentially Preventable Readmissions Classification System Definitions Manual* (Wallingford, CT: 3M HIS, October 2010), Appendix M.

classified by the clinical reason for readmission. These reasons for readmission are listed with examples in Table 1.4.1. 3M welcomes comments from physicians, hospital staff and other people with suggestions to improve the PPR logic.[11]

Several types of admissions and readmissions are categorically excluded from the PPR analysis. The most common of these in the Medicaid population are newborns. Other major examples are:

- Initial admissions for medical (i.e., non-surgical) treatment of major metastatic cancer, major trauma, human immunodeficiency virus/acquired immune deficiency syndrome (HIV/AIDS), and several less common conditions, because readmissions are very likely to be either planned or unpreventable.

- Initial admissions where the discharge status for the initial stay was “left against medical advice.”

- Initial admissions where the patient died.

- Initial admissions where the patient was transferred to another acute-care hospital. (The stay at the receiving hospital may count as an initial stay.)

Only admissions for acute care are considered for analysis. Treatment for sub-acute care, either to an acute-care hospital for rehabilitation or convalescence or to a sub-acute setting such as a nursing facility, is not considered as either an initial admission or as a readmission.

Different analysts choose different “windows” within which to calculate readmissions. The shorter the window (e.g., seven days) the more likely that a readmission is directly related to the care received during hospitalization. The longer the window (e.g., 30 days or longer), the more likely that a readmission may reflect deficiencies in patient compliance, in post-hospital care in the community, or in the patient’s baseline health status. The 15-day readmission “window” chosen for this analysis was intended to strike a balance. Section 2.7 shows readmission patterns over the course of 30 days.

1.5 Calculating PPR Rates[12]

1.5.1 Actual PPR Rate

The actual PPR rate is calculated after excluding the admissions and readmissions listed above. The actual PPR rate is calculated as:

$$\text{Actual PPR rate} = \frac{\text{PPR chains}}{\text{Initial admissions}}$$

A PPR chain starts when there is a PPR within 15 days of the discharge from the initial admission. If there is a second readmission within 15 days of the first readmission, then the chain includes two readmissions. The chain still counts only once in the numerator of the PPR rate. Note that this approach results in a lower PPR rate than if every readmission counted in the numerator.

The actual PPR rate is the number of readmission chains divided by the number of initial admissions, excluding readmissions that are not considered potentially preventable.

The actual PPR rates reported in this study are likely to be slightly understated, for two reasons.

- ***Benefit limits***. The hospital benefit for adults is subject to the limits described in Section 1.1. If a patient exhausts his or her benefit and is then readmitted within 15 days, the readmission would not appear in the analytical dataset. Because it is rare for clients to exhaust their hospital benefits, this understatement of the true PPR rate appears to be minimal.

- ***Enrollment churn.*** Clients gain and lose eligibility to Medicaid more often than is true in the Medicare and commercially-insured populations. Patients who lose or gain eligibility in the period between discharge and readmission are not fully represented in the analytical dataset. Because the PPR "window" is relatively short at 15 days, the change in enrollment also has minimal impact on the observed PPR rate.

1.5.2 Expected PPR Rate

PPR rates for a group of patients (e.g., patients treated by a particular hospital, or a population group of interest such as PCCM recipients) depend very much on the mix of clinical conditions of those patients, or casemix. A hospital with a higher PPR rate may simply treat patients who are more likely to be readmitted. Rather than reporting and comparing only actual rates, the report includes the actual rate of a group in comparison with its expected rate, which controls for four clinical characteristics that have been identified as having an important effect on PPR rates.

The expected PPR rate shows how many readmissions a hospital would be expected to have, based on its casemix.

- ***The reason for the initial admission***, that is, the base APR-DRG. A patient with pneumonia is more likely to be readmitted than a patient who delivers a baby, for example.

- ***The severity of illness***. A patient in a hospital with pneumonia and multiple complications (DRG 139-4) is more likely to be readmitted than a patient with simple pneumonia (DRG 139-1), for example.

- ***Age.*** Even for the same base APR-DRG and severity of illness, patients age 18 years of age or over are usually more likely to be readmitted than pediatric patients.

- ***Mental health/substance abuse (MH/SA) comorbidity***. Readmission is more likely if the patient has a serious mental health or substance abuse condition as a secondary diagnosis, even for medical and surgical admissions.

To enable fair comparisons among hospitals, differences in base APR-DRG, severity of illness, patient age and MH/SA comorbidity were factored into the calculation of the expected PPR rate. For this report, the expected rates are based on the experience of the entire Texas Medicaid population in SFY 2009. Hospital performance is then defined as follows, with lower values connoting better performance.

$$\text{PPR Performance Ratio} = \text{Actual/Expected Ratio} = \frac{\text{Actual PPR Rate}}{\text{Expected PPR Rate}}$$

Table 1.5.2.1 shows a simple example of how the casemix adjustment process works.

Table 1.5.2.1
Example of Calculation of Expected PPR Rate

APR-DRG	Patient Age	MH/SA Comorb.	Initial Admits	Actual Readmits	Statewide PPR Rate	MH/SA Adjustor	Expected Readmits	Actual / Expctd Ratio
123-4	Pediatric	Yes	100	7	4.3%	1.337	5.7	1.22
123-4	Pediatric	No	75	4	4.3%	0.993	3.2	1.25
123-4	Adult	Yes	50	3	5.5%	1.127	3.1	0.97
123-4	Adult	No	100	10	5.5%	0.978	5.4	1.86
432-1	Pediatric	Yes	200	12	7.8%	1.337	20.9	0.58
432-1	Pediatric	No	250	15	7.8%	0.993	19.4	0.77
432-1	Adult	Yes	150	5	9.0%	1.127	15.2	0.33
432-1	Adult	No	175	11	9.0%	0.978	15.4	0.71
All Stays			**1,100**	**67**			**88.3**	**0.76**

Explanation

- A specific hospital has 1,100 initial admissions. For example, there are 100 initial admissions with APR-DRG 123-4, a mental health/substance abuse comorbidity, and pediatric patient age.
- The hospital has a total of 67 potentially preventable readmissions, for an actual PPR rate of 67 / 1,100 = 6.1%.
- For APR-DRG 123-4, pediatric age group, a statewide PPR rate of 4.3% is assumed for purposes of this example. If a MH/SA comorbidity is present, the MH/SA adjustor is 1.337. In the first line of the table, 100 initial admissions x 0.043 x 1.337 = 5.7 expected PPRs.
- Given this hospital's casemix, total expected PPRs = 88.3, for an expected PPR rate of 88.3 / 1,100 = 8.0%.
- The hospital's PPR performance is 6.1% / 8.0% = 0.76, that is, its PPR rate is much lower than expected for a hospital with its casemix.

1.6 Interpretation of Results

The results in this study are the actual data for the entire Texas Medicaid population in SFY 2009. Because the results are not based on sample data, they need not include caveats about statistical significance so long as inferences are drawn only about the Texas Medicaid population in SFY 2009.

Results need to be interpreted very carefully for hospitals that have low volumes of Medicaid stays.

The question might be asked whether these results are accurate reflections of broader time frames, especially when results are shown for individual hospitals or other populations of interest that have small volumes of inpatient stays. For example, consider a hospital with 50 initial admissions. If it has two readmission chains, then its PPR rate would be 4%, about the same as the statewide rate. If it has just one additional readmission chain, then its PPR rate would be 6%, noticeably higher than the statewide rate.

Two aspects of our methodology lessen the potentially misleading effects of analyzing relatively small numbers of stays.

- ***Low-volume hospitals.*** A hospital is defined as "low volume" if it does not have at least 40 initial admissions, at least 5 actual readmissions, and at least 5 expected readmissions. Because readmissions are infrequent events for many common conditions, hospitals with as many as 75 or 100 initial admissions will usually be defined as low-volume because they will have fewer than 5 expected readmissions. Results for low-volume hospitals are reported to the hospital themselves, but are not evaluated for statistical significance and are not included in the discussion of statewide patterns in Section 2.6.

- ***Test of statistical significance.*** Although results for each hospital are complete for SFY 2009, a test of statistical significance can suggest whether the SFY 2009 results might also apply to a broader time frame. Statistical significance depends on two factors: the number of stays and the difference between actual readmissions and expected readmissions. Intuitively, there would be more confidence that the "true" rate is higher than expected when the actual/expected ratio is 1.40 than when the rate is 1.12. Similarly, there would be an expectation that a given rate would be more stable if it is for 5,000 stays than if it is for 100 stays. In Section 2.6 the significance of hospital-specific actual/expected ratios is tested using the Cochrane-Mantel-Haenszel test of conditional independence.[13] The number of hospitals where the difference between the PPR performance ratio and 1.00 is statistically significant is also shown, using the 90% confidence level.

2 Statewide Results

2.1 Overall PPR Results

In SFY 2009, there were 329,905 initial stays within the scope of this analysis (Table 2.1.1). These initial stays were followed by 14,318 potentially preventable readmissions in 11,796 PPR chains. The overall PPR rate was 3.6% (= 11,796/329,905). About two-thirds of readmissions were to the same hospital.

Excluding newborns, the PPR rate in the Medicaid population is 3.6% overall, 0.8% for obstetrics, 3.9% for non-obstetric pediatrics and 8.2% for non-obstetric adult stays

Medicaid payments for PPRs totaled \$104 million (Table 2.1.2). About 3.5% of all Medicaid payments for hospital care are for PPR.[14] This figure covers only the Medicaid payment to the hospital, not the cost to the hospital itself, the cost of physician and other associated services, or the cost to the patient.

Chart 2.1.1 compares Texas Medicaid results with results from a similar analysis done by the Florida Agency for Health Care Administration. The Florida analysis included not only Medicaid, but other payers as well. To make the Florida all-patient data comparable to the results presented here, TMHP recalculated the Florida data to reflect the same distribution of APR-DRGs by age that are seen in the

Table 2.1.1
PPR Rates Overall and by Medicaid Care Category

			Total Readmissions			
Medicaid Care Category	**Initial Admits**	**Readmit Chains**	**Same Hospital**	**Other Hospital**	**All**	**PPR Rate**
Pediatric						
Respiratory	26,517	649	552	170	722	2.4%
Other medical	39,849	1,223	1,073	389	1,462	3.1%
Other surgical	10,404	470	442	89	531	4.5%
MH/SA	12,843	1,181	871	593	1,464	9.2%
Subtotal	**89,613**	**3,523**	**2,938**	**1,241**	**4,179**	**3.9%**
Adult						
Circulatory	12,565	1,025	835	409	1,244	8.2%
Other medical	45,377	3,618	2,914	1,517	4,431	8.0%
Other surgical	16,493	1,005	914	243	1,157	6.1%
MH/SA	12,036	1,445	1,112	978	2,090	12.0%
Subtotal	**86,471**	**7,093**	**5,775**	**3,147**	**8,922**	**8.2%**
Obstetrics	153,821	1,180	1,001	216	1,217	0.8%
Total	**329,905**	**11,796**	**9,714**	**4,604**	**14,318**	**3.6%**

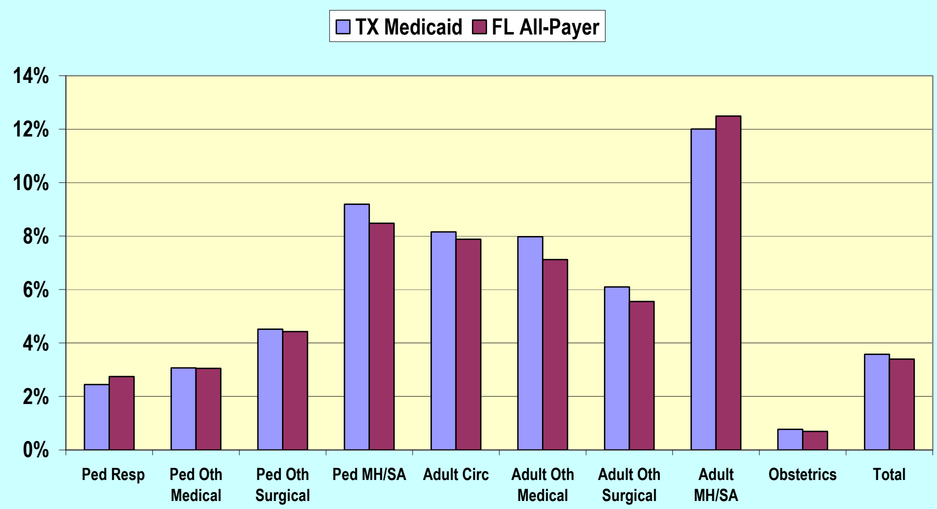
Notes
1) MH/SA = mental health and substance abuse
2) 329,905 initial stays + 14,318 readmissions = 344,223 stays in the analytical dataset.

Texas Medicaid dataset. The chart shows that the similarities between the two sets of results are much more notable than the differences, despite the differences in states, time periods and populations. This finding implies that patterns of readmission seen in this study are not unique to the Texas Medicaid population.

The Texas Medicaid PPR rate of 3.6% may seem low, especially in comparison with the widely-reported finding that 20% of Medicare patients are readmitted within 30 days.[15] Reasons for the difference include the longer readmission window used by Medicare (30 days instead of 15 days), the broader definition of readmission (all-cause for Medicare) and the very different casemixes of the two populations. In particular, almost half of all Texas stays in this analysis are for obstetrics, where the PPR rate was very low (0.8%). For the non-obstetric pediatric population, the PPR rate was 3.9%; for the non-obstetric adult population, the PPR rate was 8.2%. For some DRGs, the PPR rates approached 15% or even 20%. This will be shown in Section 2.4.

Readmissions for people initially admitted with mental health or substance abuse diagnoses are particularly notable. Almost 10% of pediatric patients and 12% of adult patients with these conditions are back in the hospital within 15 days. Moreover, patients in these care categories are more likely to have more than one readmission within a chain of readmissions, as shown in Table 2.1.2. Pediatric patients with at least one readmission have 1.2 readmissions on average; adults with at least one readmission have 1.3 readmissions on average. Presence of a serious mental health or substance abuse condition as a secondary diagnosis also makes readmissions more likely for patients admitted with medical or surgical conditions, as will be shown in Section 2.5.

Chart 2.1.1
Comparison of Results: Texas Medicaid vs. Florida All-Payer



Florida results have been made comparable to Texas results through adjustment for frequency by APR-DRG and adult/pediatric age split,

Table 2.1.2 Hospital Charges and Medicaid Payments for PPRs							
				Totals for PPR Stays			
Medicaid Care Category	PPR Chains	PPR Stays	Stays per Chain	Days	Days / Stay	Hospital Charges (Millions)	Medicaid Payments (Millions)
Pediatric							
Respiratory	649	722	1.1	5,019	7.0	$37.6	$11.7
Other medical	1,223	1,462	1.2	11,561	7.9	$73.6	$24.2
Other surgical	470	531	1.1	4,554	8.6	$30.0	$9.1
MH/SA	1,181	1,464	1.2	19,329	13.2	$27.9	$10.7
Subtotal	**3,523**	**4,179**	**1.2**	**40,463**	**9.7**	**$169.1**	**$55.7**
Adult							
Circulatory	1,025	1,244	1.2	6,806	5.5	$43.7	$6.6
Other medical	3,618	4,431	1.2	27,223	6.1	$156.2	$22.8
Other surgical	1,005	1,157	1.2	7,930	6.9	$47.4	$6.9
MH/SA	1,445	2,090	1.4	14,107	6.7	$31.0	$8.1
Subtotal	**7,093**	**8,922**	**1.3**	**56,066**	**6.3**	**$278.2**	**$44.4**
Obstetrics	1,180	1,217	1.0	4,222	3.5	$22.7	$4.0
Total	**11,796**	**14,318**	**1.2**	**100,751**	**7.0**	**$470.1**	**$104.0**

2.2 Results by Delivery Method

Table 2.2.1 shows the results by delivery method, that is, FFS compared with PCCM and MCO. The actual PPR rates are 5.4%, 3.5%, and 2.3% respectively. These unadjusted rates are misleading, however, since they do not take into account the very different populations within the three delivery methods. To take into account differences in casemix, the actual PPR was compared with the expected PPR rate. The result is that the PPR performance of the FFS sector is about as expected (actual PPR chains are 2% higher than expected). In the PCCM sector, the actual number of PPR chains is 5% lower than expected. In the managed care sector, the actual number of PPRs claims is 6% higher than expected. When looking at the individual care categories, however, the managed care sector has the lowest ratio of actual to expected PPRs in four of the nine care categories. The relatively high actual/expected ratios in the pediatric and adult mental health and substance abuse categories are what make the managed care actual/expected PPR ratio higher overall than the other two sectors.

The number of PPR chains is about as expected in the FFS sector, 5% lower than expected in the PCCM sector and 6% higher than expected in the managed care sector.

These findings do not necessarily reflect differences in how hospital care is managed under the three delivery methods. For example, the differences in PPR rates may reflect a difference in the mix of hospitals used by each program or they may reflect unmeasured differences in the population served. Further research would be appropriate in order to understand this question.

Table 2.2.1

PPR Results by Health Care Delivery Method

	Fee-for-Service				Primary Care Case Management				Managed Care Organization			
Medicaid Care Category	Initial Admits	Actual PPR Rate	Expctd PPR Rate	Actual / Expctd Ratio	Initial Admits	Actual PPR Rate	Expctd PPR Rate	Actual / Expctd Ratio	Initial Admits	Actual PPR Rate	Expct d PPR Rate	Actual / Expctd Ratio
Pediatric												
Respiratory	7,442	3.0%	2.9%	1.05	10,259	2.2%	2.2%	0.98	8,816	2.3%	2.3%	0.98
Other medical	11,937	4.0%	3.7%	1.07	13,942	2.6%	2.7%	0.96	13,970	2.8%	2.9%	0.97
Other surgical	4,532	5.6%	4.9%	1.12	2,992	4.2%	4.4%	0.97	2,880	3.2%	4.1%	0.78
MH/SA	4,766	9.2%	9.3%	0.99	3,390	7.0%	8.7%	0.80	4,687	10.8%	9.4%	1.14
Subtotal	**28,677**	**4.8%**	**4.6%**	**1.05**	**30,583**	**3.1%**	**3.4%**	**0.92**	**30,353**	**3.9%**	**3.9%**	**1.02**
Adult												
Circulatory	5,372	8.1%	8.3%	0.98	7,011	8.3%	8.1%	1.02	182	6.0%	7.1%	0.85
Other medical	20,900	8.4%	8.0%	1.04	22,360	7.9%	8.1%	0.98	2,117	4.4%	5.6%	0.78
Other surgical	8,669	6.2%	6.2%	1.00	6,873	6.4%	6.2%	1.03	951	2.9%	4.5%	0.65
MH/SA	3,602	10.8%	11.4%	0.94	2,836	9.1%	11.5%	0.79	5,598	14.3%	12.6%	1.13
Subtotal	**38,543**	**8.1%**	**8.0%**	**1.01**	**39,080**	**7.8%**	**8.0%**	**0.97**	**8,848**	**10.5%**	**10.0%**	**1.06**
Obstetrics	17,408	0.6%	0.8%	0.82	53,472	0.7%	0.8%	0.87	82,941	0.8%	0.8%	1.13
Total	**84,628**	**5.4%**	**5.4%**	**1.02**	**123,135**	**3.5%**	**3.7%**	**0.95**	**122,142**	**2.3%**	**2.2%**	**1.06**

Note: Actual/expected ratios were calculated using more decimal places in the actual and expected PPR rates than are shown here.

2.3 Reasons for Potentially Preventable Readmissions

Table 2.3.1 categorizes the clinical reasons for readmission. Of the 14,318 total readmissions:

- 23% were medical readmissions for the same condition as the initial admission.
- 29% were medical readmissions for a different acute condition that could plausibly have had a clinical association with the initial admission.
- 24% were mental health or substance abuse readmissions that followed an initial admission for mental health or substance abuse.
- Only 2% of readmissions were for post-surgical complications.

The most common reasons for readmission, in roughly equal proportions, are medical readmissions for the same condition, medical readmissions for other acute conditions, and readmissions for mental illness or substance abuse.

These results, which echo results from Florida and elsewhere, strongly imply that the main issue in

Table 2.3.1

Potentially Preventable Readmissions, Percentage Split by Clinical Reason

Medicaid Care Category	Potentially Preventable Readmissions	1 Medical readmission for recurrence	2A Ambulatory care sensitive condition	2B Readmission for chronic problem	3 Medical readmission for acute condition	4 Surgical readmission for recurrence	5 Surgical readmission for complication	6A MH readmission after initial admission not MH/SA	6B SA readmission after initial admission not MH/SA	6C MH/SA readmission after initial MH/SA admission
Pediatric										
Respiratory	722	51%	19%	12%	17%	0%	0%	0%	0%	0%
Other medical	1,462	45%	13%	11%	26%	0%	1%	4%	0%	0%
Other surgical	531	3%	10%	8%	56%	12%	9%	1%	0%	0%
MH/SA	1,464	0%	1%	1%	1%	0%	0%	0%	0%	97%
Subtotal	**4,179**	**25%**	**9%**	**7%**	**20%**	**2%**	**2%**	**2%**	**0%**	**34%**
Adult										
Circulatory	1,244	37%	16%	8%	27%	3%	4%	5%	1%	0%
Other medical	4,431	38%	16%	12%	25%	0%	1%	6%	1%	2%
Other surgical	1,157	5%	13%	7%	52%	8%	11%	2%	1%	0%
MH/SA	2,090	0%	1%	2%	3%	0%	0%	0%	0%	93%
Subtotal	**8,922**	**25%**	**12%**	**8%**	**23%**	**1%**	**2%**	**4%**	**1%**	**23%**
Obstetrics	1,217	1%	0%	0%	98%	0%	0%	0%	0%	0%
Total	**14,318**	**23%**	**11%**	**7%**	**29%**	**1%**	**2%**	**3%**	**1%**	**24%**

Note: MH=mental health; SA=substance abuse readmissions lies not in procedural errors (e.g., leaving a sponge in a patient) but rather in fully resolving the initial medical complaint and creating an effective transition from the hospital to care in the community or a post-acute facility.

2.4 Results by APR-DRG

The three tables in this section show results by base APR-DRG, sorted in three different ways. In each table, the DRG shown is the base DRG, without level of severity (e.g., APR-DRG 139 for pneumonia, not APR-DRG 139-1 for pneumonia, severity 1).

These three tables by DRG highlight the issues of readmissions for mental health, substance abuse, and liver disorders.

Table 2.4.1 shows the top DRGs in terms of total potentially preventable readmissions. This table is most relevant when addressing the question of how to reduce PPRs in total. The importance of individual mental health DRGs is evident: these DRGs have both high PPR rates and high PPR volumes. The number of

Table 2.4.1
PPR Rates by APR-DRG: Top 20 APR-DRGs in Terms of Total Readmissions

Base DRG	Initial Admits	Readmit Chains	Readmit Stays	Stays per Chain	PPR Rate
753 Bipolar Disorders	11,283	1,176	1,530	1.3	10.42%
750 Schizophrenia	5,082	745	1,129	1.5	14.66%
751 Major Depression	4,998	475	615	1.3	9.50%
540 Cesarean Delivery	41,035	565	577	1.0	1.38%
560 Vaginal Delivery	91,865	543	560	1.0	0.59%
194 Heart Failure	2,861	291	369	1.3	10.17%
140 COPD	3,188	301	355	1.2	9.44%
139 Other Pneumonia	9,990	296	339	1.1	2.96%
420 Diabetes	2,535	187	266	1.4	7.38%
138 Bronchiolitis & RSV Pneumonia	9,270	236	252	1.1	2.55%
662 Sickle Cell Anemia Crisis	1,611	177	252	1.4	10.99%
720 Septicemia & Disseminated Infections	2,335	192	226	1.2	8.22%
053 Seizure	3,808	167	209	1.3	4.39%
249 Non-Bacterial Gastroenteritis	5,673	162	195	1.2	2.86%
279 Hepatic Coma & Other Major Liver Disorders	737	139	190	1.4	18.86%
280 Alcoholic Liver Disease	765	147	188	1.3	19.22%
383 Cellulitis & Other Bacterial Skin Infections	6,492	168	178	1.1	2.59%
460 Renal Failure	1,431	137	167	1.2	9.57%
463 Kidney & Urinary Tract Infections	4,572	140	163	1.2	3.06%
282 Disorders of Pancreas except Malignancy	1,338	118	155	1.3	8.82%

Notes
1) The APR-DRG shown is the DRG for the initial admission.
2) COPD=chronic obstructive pulmonary disease; RSV= respiratory syncytial virus

PPRs for obstetric stays, by contrast, is high only because there are so many obstetric admissions. The PPR rates themselves are very low.

This table also illustrates the importance of using a PPR measurement methodology that includes conditions common in the Medicaid population. The table shows that heart failure and pneumonia do generate many readmissions (as in Medicare) but that the mental health DRGs are a larger PPR issue in a Medicaid population.

Table 2.4.2 shows the top DRGs in terms of initial admissions. These are the most common reasons why Medicaid clients are admitted to hospital (excluding newborns). The low PPR rates for obstetric DRGs are notable.

Table 2.4.2

PPR Rates by APR-DRG: Top 20 APR-DRGs in Terms of Initial Admissions

Description	Initial Admits	Readmit Chains	Readmit Stays	Stays per Chain	PPR Rate
560 Vaginal Delivery	91,865	543	560	1.0	0.59%
540 Cesarean Delivery	41,035	565	577	1.0	1.38%
753 Bipolar Disorders	11,283	1,176	1,530	1.3	10.42%
139 Other Pneumonia	9,990	296	339	1.1	2.96%
138 Bronchiolitis & RSV Pneumonia	9,270	236	252	1.1	2.55%
566 Other Antepartum Diagnoses	9,247	5	5	1.0	0.05%
383 Cellulitis & Other Bacterial Skin Infections	6,492	168	178	1.1	2.59%
141 Asthma	6,400	121	134	1.1	1.89%
750 Schizophrenia	5,082	745	1,129	1.5	14.66%
249 Non-Bacterial Gastroenteritis	5,673	162	195	1.2	2.86%
751 Major Depression	4,998	475	615	1.3	9.50%
541 Vaginal Delivery w Sterilization &/or D&C	4,725	31	33	1.1	0.66%
463 Kidney & Urinary Tract Infections	4,572	140	163	1.2	3.06%
053 Seizure	3,808	167	209	1.3	4.39%
140 COPD	3,188	301	355	1.2	9.44%
113 Infections of Upper Respiratory Tract	3,245	85	93	1.1	2.62%
194 Heart Failure	2,861	291	369	1.3	10.17%
563 Threatened Abortion	2,951	-	-	-	0.00%
225 Appendectomy	2,757	112	123	1.1	4.06%
420 Diabetes	2,535	187	266	1.4	7.38%

Notes

1) The APR-DRG shown is the DRG for the initial admission.

2) RSV=respiratory syncytial virus; D&C=dilatation and curettage; COPD=chronic obstructive pulmonary disease

Table 2.4.3 shows the DRGs with the highest PPR rates (so long as the DRG met minimum volume requirements for the number of stays). A hospital would find this table useful in setting flags for readmission risk by DRG. Although the volumes of initial admissions for the liver diseases and cardiovascular procedures are low, any patient in one of these DRGs is clearly at high risk for a potentially preventable readmission.

Table 2.4.3

PPR Rates by APR-DRG: Top 20 APR-DRGs in Terms of PPR Rates

Base DRG	Initial Admits	Readmit Chains	Readmit Stays	Stays per Chain	PPR Rate
280 Alcoholic Liver Disease	765	147	188	1.3	19.22%
279 Hepatic Coma & Other Major Liver Disorders	737	139	190	1.4	18.86%
260 Major Pancreas & Liver Procedures	123	20	30	1.5	16.26%
165 Coronary Bypass w Catheterization	302	45	51	1.1	14.90%
750 Schizophrenia	5,082	745	1,129	1.5	14.66%
261 Major Biliary Tract Procedures	56	8	11	1.4	14.29%
162 Cardiac Valve Procedures w Catheterization	58	8	9	1.1	13.79%
510 Radical Hysterectomy	45	6	6	1.0	13.33%
283 Other Disorders of the Liver	820	103	131	1.3	12.56%
206 Complications of CV Device or Procedure	211	26	41	1.6	12.32%
048 Nerve Disorders	524	63	84	1.3	12.02%
312 Skin Graft For Connective Tissue Diagnoses	42	5	6	1.2	11.90%
220 Major Stomach & Esophageal Procedures	295	35	40	1.1	11.86%
169 Major Vascular Procedures	203	24	27	1.1	11.82%
163 Cardiac Valve Procedures w/o Catheterization	174	20	20	1.0	11.49%
245 Inflammatory Bowel Disease	260	29	36	1.2	11.15%
022 Ventricular Shunt Procedures	386	43	48	1.1	11.14%
662 Sickle Cell Anemia Crisis	1,611	177	252	1.4	10.99%
134 Pulmonary Embolism	291	31	39	1.3	10.65%
130 Respiratory System Diagnoses w MV 96+ Hrs	700	73	82	1.1	10.43%

Notes

1) The APR-DRG shown is the DRG for the initial admission.

2) A DRG is only included in this table if there were at least 40 initial admissions and at least five actual readmission chains.

3) CV=cardiovascular; MV=mechanical ventilation

2.5 The Importance of Casemix Adjustment

The tables in Section 2.4 demonstrate the importance of the base DRG in understanding PPR rates. Any comparison of PPR rates, for example between hospitals, managed care plans or eligibility groups, is fundamentally flawed if it does not adjust for differences in the mix of base DRGs. As described in Section 1.5, adjustment was made for three other aspects of casemix in comparing subsets of the analytical dataset. In each case, our findings echo those from similar analysis in Florida.

PPR rates are influenced by the level of severity, the patient age and the presence of a serious mental health or substance abuse comorbidity.

- ***Severity of illness.*** In general, the risk of readmission increases with the severity of illness for any given condition. Table 2.5.1 shows the top 10 DRGs in terms of total readmissions (from Table 2.4.1.) In most cases, the PPR rates increase as patient severity of illness increases within the base DRG. The pattern is especially evident for the medical DRGs, such as heart failure,

Table 2.5.1

Initial Admissions and PPR Rates by Level of Severity for the Top 10 Base DRGs in Terms of Total Readmissions

Base DRG		Total	Level of Severity			
			Severity 1	Severity 2	Severity 3	Severity 4
753 Bipolar Disorders	Initial Admits	11,283	5,870	5,140	266	7
	PPR Rate	10.4%	10.1%	10.8%	11.7%	0.0%
750 Schizophrenia	Initial Admits	5,082	2,265	2,534	278	5
	PPR Rate	14.7%	15.3%	13.8%	17.3%	0.0%
751 Major Depression	Initial Admits	4,998	1,999	2,833	162	4
	PPR Rate	9.5%	8.7%	10.0%	11.1%	50.0%
540 Cesarean Delivery	Initial Admits	41,035	30,286	8,284	2,337	128
	PPR Rate	1.4%	1.1%	2.0%	3.0%	3.1%
560 Vaginal Delivery	Initial Admits	91,865	63,323	24,611	3,878	53
	PPR Rate	0.6%	0.5%	0.7%	1.5%	1.9%
194 Heart Failure	Initial Admits	2,861	273	1,448	981	159
	PPR Rate	10.2%	8.1%	9.9%	11.4%	8.8%
140 COPD	Initial Admits	3,188	665	1,557	857	109
	PPR Rate	9.4%	7.2%	9.8%	9.7%	15.6%
139 Other Pneumonia	Initial Admits	9,990	4,381	4,078	1,309	222
	PPR Rate	3.0%	1.3%	3.3%	6.4%	9.9%
420 Diabetes	Initial Admits	2,535	586	1,384	493	72
	PPR Rate	7.4%	5.1%	7.7%	8.9%	8.3%
138 Bronchiolitis & RSV Pneum	Initial Admits	9,270	5,841	3,015	359	55
	PPR Rate	2.6%	2.1%	2.8%	5.3%	12.7%

COPD, pneumonia, diabetes and bronchiolitis.

- ***Age.*** Excluding the obstetrics stays, approximately half of all stays in the present analysis are for clients 17 years of age and younger. Even after controlling for APR-DRG, pediatric age tends to make a readmission less likely. Chart 2.5.1 shows this pattern for ten DRGs that are common in both the adult and pediatric populations. The pattern also holds true in general, although not for every DRG. Because of the large number of pediatric stays, statewide PPR averages for every DRG were calculated separately for the adult and pediatric populations.

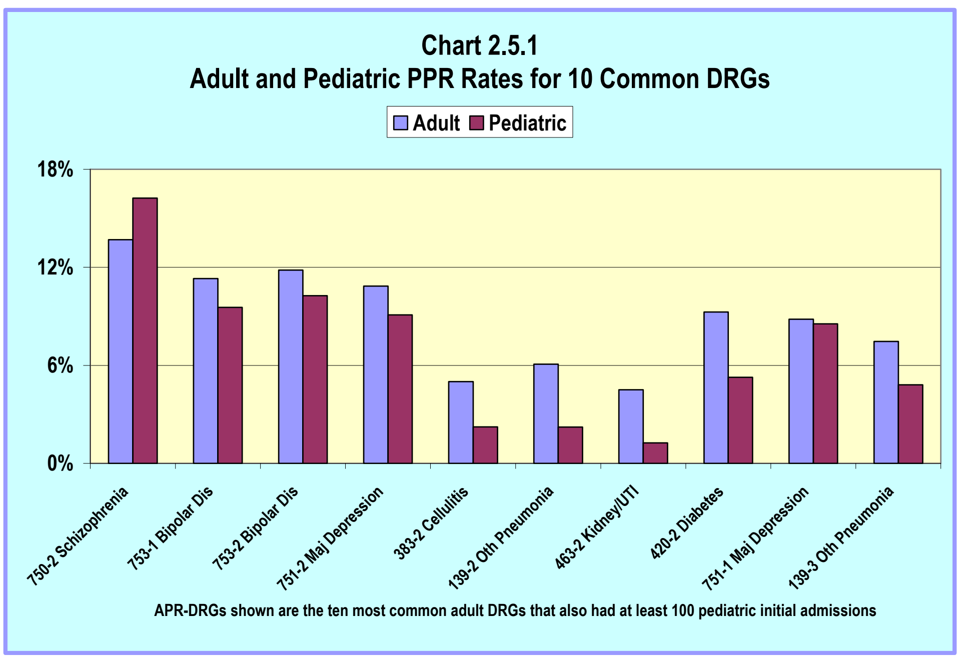
- ***Presence of a serious mental health or substance abuse co-morbidity***. Patients admitted with medical or surgical conditions are more likely to be readmitted if the claim for the initial admission also shows a secondary diagnosis of serious mental illness or substance abuse. For adults, a readmission becomes 15% more likely; for pediatrics, 35% more likely (Table 2.5.2).

Table 2.5.2
Adjustment for MH/SA Comorbidity

Age Category	MH/SA Comorbidity	Adj. Factor
Pediatric	No	0.993
Pediatric	Yes	1.337
Adult	No	0.978
Adult	Yes	1.127

Note: In calculating expected PPR rates, the adjustment factor is applied only to medical and surgical admissions, not to MH/SA or obstetric admissions

While these factors are believed to be important in understanding the incidence of PPRs, the possibility that there are other, unmeasured factors that systematically affect PPR incidence should be noted.



2.6 PPR Performance by Hospital

To compare hospitals in PPR performance, the actual PPR rate and expected PPR rates for each hospital were calculated, as explained in Section 1.5. If the actual/expected ratio was less than 1.00, then the hospital had fewer PPRs than would be expected for a hospital with the same casemix. That is, the result was better than expected.

Excluding low-volume hospitals, 84 of 230 hospitals had PPR results about as expected, while 69 hospitals had results lower than expected and 77 hospitals had results higher than expected.

In comparing performance, all hospitals with low volumes were excluded. As explained in Section 1.5.2, this was done because hospitals with low volumes can have unstable results based on the absence or presence of one or two readmissions.

Table 2.6.1 shows TMHP's interpretation of the calculated results. Of 230 hospitals with sufficient volume to be considered, 84 had a rate within 10% of the expected rate, which was considered "about as expected." Another 69 hospitals had a rate below a threshold of 10% less than expected, while 77 hospitals had a rate above a threshold of 10% more than expected. The word "expected" is used in the sense that it reflects the calculation of the Texas overall statewide Medicaid PPR rate in SFY 2009 and then uses that rate as the norm. An alternative approach would be to define a norm that can be achieved by hospitals following best practices, and then use that norm as the "expected" value. At this time, there has not been sufficient research with PPRs to provide an accepted best-practice norm.

In statistical terms, these were the actual results for SFY 2009, and are not based on a sample. Therefore the results are accurate for every hospital. Without doing another full analysis, it is impossible to know whether the results for a particular hospital would have been different if another time period had been selected. A test of statistical significance, however, can suggest the likely answer (see Section 1.6). It makes sense that those hospitals whose actual/expected PPR ratios were furthest away from 1.00 also tended to have statistically significant differences from 1.00.[16]

Table 2.6.1
Number of Hospitals by PPR Performance

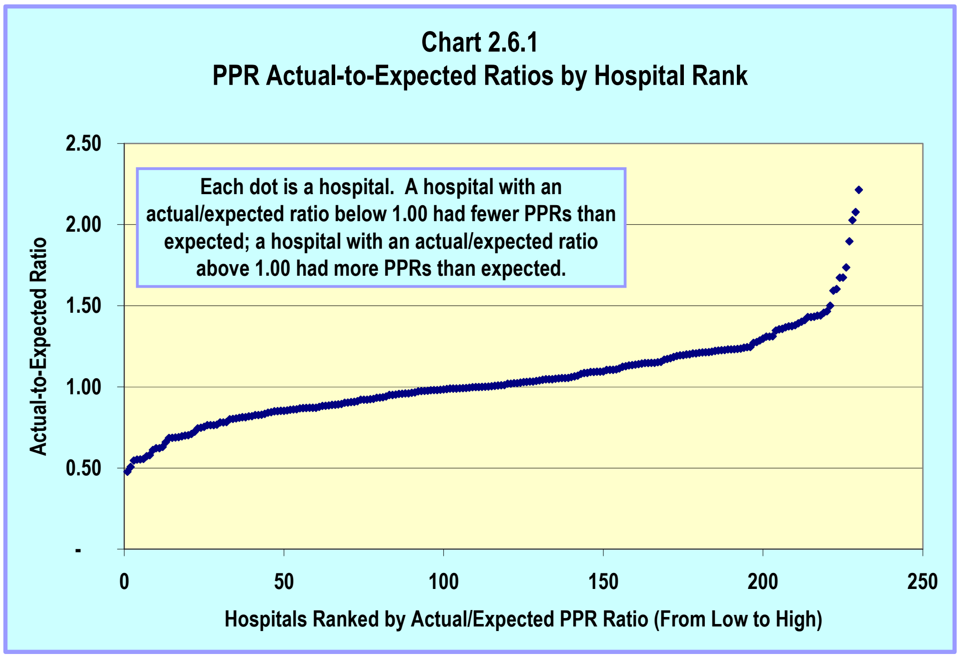
Ratio of Actual PPRs to Expected PPRs	Interpretation	Hospitals	Stat Sig Diff
Lower than 0.75	Much lower than expected	24	12
0.75 to 0.89	Lower than expected	45	7
0.90-1.10	About as expected	84	0
1.11 to 1.25	Higher than expected	43	9
Higher than 1.25	Much higher than expected	34	21
Total		**230**	**49**

Notes

1. Low-volume hospitals are excluded. Low-volume hospitals do not meet the criteria of having at least 40 initial admissions, at least 5 expected readmissions, and at least 5 actual readmissions.

2. "Stat Sig Diff" shows the number of hospitals where the difference from 1.00 is statistically significant at the 90% confidence level.

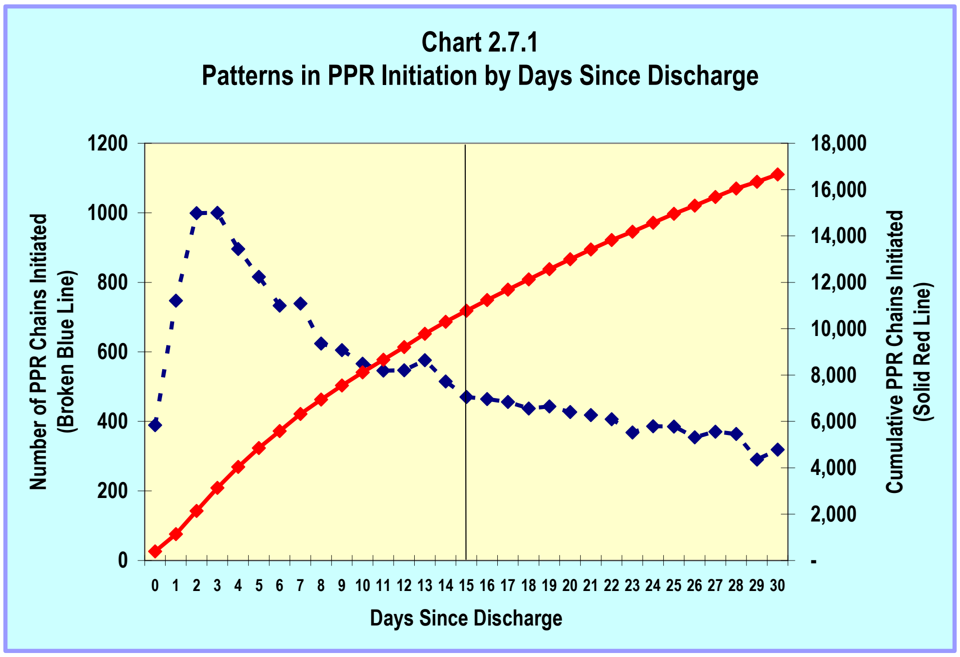
For these 230 hospitals, Chart 2.6.1 shows the range of results. The best-performing hospital had a performance ratio of 0.48, which is about half as high as the median hospital. The worst-performing hospital had a performance ratio of 2.21, which is about twice as high as the median hospital. If a broader time period were chosen, it is likely that the range of results would be narrower due to the statistical phenomenon of regression to the mean. (That is, some hospitals at the lower or upper ends of the range simply had a good or bad year in SFY 2009.) However, the range in hospital performance is wide enough to suggest that opportunities exist for hospitals to learn from one another in reducing potentially preventable readmissions.



2.7 Readmission Patterns by Days from Discharge

As noted earlier, different analysts choose different time frames within which to calculate readmissions. For this report, a 15 day time frame, or "window," was used. A window of 30 days is also commonly used. If this analysis had been done using a 30-day window, the result would have been a PPR rate of 5.1%, as opposed to the 3.6% rate shown in Table 2.1.1. Chart 2.7.1 shows the patterns in PPRs by days since discharge using a 30-day window. The second and third days after discharge are the most likely days for potentially preventable readmissions. The likelihood of readmission then falls sharply after that (the broken line). Of all readmission chains within the 30-day window, about two-thirds start within 15 days (the solid line).

The second and third days after discharge are the most likely days for readmission.



3 Frequently Asked Questions

1. What counts as a potentially preventable readmission (PPR)?

A PPR is a readmission that has a plausible clinical connection to the initial admission and potentially could have been prevented. This definition includes not only readmissions for the same conditions and for surgical complications but also readmissions that are sensitive to ambulatory care outside the hospital, including for mental health and substance abuse conditions. Readmissions do not count as PPRs if they are likely planned (e.g., major metastatic cancer), likely unavoidable (e.g., HIV/AIDS), clearly involve patient compliance issues (e.g., self-discharge against medical advice), or are clearly unrelated (e.g., hip fracture after heart attack). The PPR count includes both readmissions to the same hospital and readmissions to a different hospital.

2. Who developed the PPR methodology? Who else uses it?

The specific PPR methodology used in this analysis was developed by 3M Health Information Systems. It has also been used by the Florida Agency for Health Care Administration (www.floridahealthfinder.gov), the Maryland Health Services Cost Review Commission, the New York Medicaid program, a number of other state agencies, and the Medicare Payment Advisory Commission.

3. Why were APR-DRGs, and not Medicare MS-DRGs, used to measure casemix?

The Medicare MS-DRG algorithm was designed only for the Medicare population.[17] The APR-DRG algorithm was designed for use with an all-patient population and fits a Medicaid

Table 3.1
Principal Differences Between Medicare and Texas Medicaid Approaches to Measuring Readmissions

	Medicare	Texas Medicaid
Population	Fee-for-service Medicare age 65 and over	Fee for service and managed care Medicaid, all ages except newborns
Readmission window	30 days	15 days
Results based on	July 2006-June 2009	SFY 2009 (September 2008-August 2009)
Conditions included	Heart attack, heart failure, pneumonia	All (with minor exceptions)
Readmissions included	All	Only those with a plausible clinical connection to the initial admission
Methodology	Multivariate regression	Categorical
Methodology developed by	Team of researchers from Yale University research center, for the Centers for Medicare and Medicaid Services (CMS)	3M Health Information Systems
Adjustments for casemix	Age, gender, comorbidities at time of initial admission, medical history within the past year	Base APR-DRG, APR-DRG severity of illness, presence of a MH/SA comorbidity, age
Availability of results	Hospital-specific data available at www.hospitalcompare.gov	Hospital-specific data provided confidentially only to each hospital

Note: Details of the Medicare methodology are available at www.hospitalcompare.hhs.gov/staticpages/for-professionals/ooc/calculation-of-30-day-risk.aspx and at www.qualitynet.org.

population well.[18] The 3M PPR methodology was designed to be applied to APR-DRGs.

4. Is this the same approach that Medicare has taken? What is the difference?

The two approaches and the context in which they are applied are quite different, as summarized in Table 3.1. The four main reasons why this approach was chosen are:

- The Texas Legislature specifically required use of a measure that focuses on "potentially preventable" readmissions, as opposed to readmissions from all causes.
- The PPR methodology used for this report is applicable across multiple conditions, whereas the Medicare method focuses on one condition at a time and has been developed for only three conditions: heart attack, heart failure and pneumonia.
- The Medicare methodology was designed for a Medicare population in terms of the conditions studied, the casemix adjustors applied, and the nature of the data used. The three conditions for which the Medicare methodology was developed are not the most important conditions for a Medicaid population.
- The PPR methodology provides individual hospitals with specific admission-level results that are more useful and easier for non-statisticians to understand than the Medicare methodology.

5. How does coding on the claim form (UB-04 CMS-1450 or X12N 837I) affect casemix measurement and PPR results?

PPRs are identified by comparing the base APR-DRG for the initial stay with the base APR-DRG for the readmission. In addition, the risk of readmission, and therefore the hospital's performance in comparison with the statewide average, also depends on the APR-DRG severity of illness assigned to each stay. The assignment of both the base APR-DRG and the severity of illness depend on the number, nature and interaction of ICD-9-CM diagnoses and procedures coded by the hospital on the claim. (There is no single list of complications and comorbidities, as there is under Medicare.) Hospitals are therefore advised to code each claim thoroughly so that the APR-DRG assignment is as accurate as possible. Hospitals need not list the DRG on the claim as the APR-DRG assignment is done by TMHP as part of the PPR analysis.

Refer to appendix Section A.2.4 for a discussion of coding completeness in the analytical dataset. A review of the claims data used for this analysis found no obvious issues in coding completeness, except that specialty psychiatric hospitals may not be as thorough in assigning diagnosis and procedure codes as general hospitals serving similar patients.

6. I disagree that seizure should be considered a potentially preventable readmission when the patient was initially admitted for asthma. How do I make my point?

An advantage of the PPR methodology is its transparency, which enables clinicians to understand in detail what circumstances do and do not count as a potentially preventable readmission. In particular, Appendix M of the *PPR Definitions Manual* lists the admission/readmission APR-DRGs pairs that are considered to be potentially preventable readmissions. 3M Health Information Systems welcomes suggestions to refine the methodology. These may be sent to Gregg Perfetto at gmperfetto@mmm.com.

7. What steps were taken to adjust for differences in casemix among hospitals?

The likelihood of readmission is influenced by the reason for the initial admission, the severity of the patient's condition, the presence or absence of a serious mental health or substance abuse comorbidity, and the patient's age (17 years of age and younger, or 18 years of age and over). Comparisons of subsets of the analytical dataset (e.g., across hospitals) are adjusted for these differences in casemix. Refer to Section 1.5 and the methodological appendix.

8. My hospital provides only pediatric services. How can our PPR rate be compared with that of other hospitals?

One reason why the 3M PPR methodology was used was because of the large volume of pediatric, obstetric and young adult inpatient stays in the Texas Medicaid population. APR-DRGs, which were developed by 3M and the National Association of Children's Hospitals and Related Institutions, are a highly valid measure of pediatric casemix. The PPR methodology used also adjusts for statewide differences in PPR rates between clients under 18 years old and adults.

9. Are the results statistically significant?

Results are based on complete data for SFY 2009, not on a sampling methodology. There is no question of statistical significance as long as inferences are made only about the Texas Medicaid population in SFY 2009. In a different time period, the results might be different, especially when a hospital had a small volume of stays in SFY 2009. To assess this likelihood, a categorical statistic called the Cochran-Mantel-Haenszel (CMH) statistic was used. Refer to Section 1.5 and appendix Section A.6.

10. Why was a multivariate regression analysis not used? Medicare follows this approach.

Both categorical analysis (this approach) and multivariate regression analysis (the Medicare approach) are valid ways to analyze readmissions. A categorical approach is considered by many to be more accessible to people not trained in statistics, enabling a broader understanding and acceptance of the information. This understanding helps hospitals reduce their readmission rates.

11. How were hospitals identified in the analysis?

Hospitals were identified by their Texas Provider Identifier (TPI) number, which is submitted by hospitals on FFS and PCCM claims that are paid directly by the Texas Medicaid program. (In some cases, two TPIs for the same hospital were consolidated into a single TPI for purposes of this analysis, for example if the hospital received a new TPI part-way through SFY 2009.)

Encounter claims from managed care organizations show the hospital's National Provider Identifier (NPI) rather than its TPI. Each claim was crosswalked to the appropriate TPI, using data fields such as the NPI, taxonomy, type of bill, and zip code. In 129 situations involving 1,388 claims, an appropriate TPI assignment could not be made with a high degree of confidence. These 1,388 claims, representing 1% of the managed care claims in the analytical dataset, were excluded from further analysis.

12. Can my hospital appeal the finding of individual readmissions being potentially preventable?

No. In the approach taken here, what matters is a hospital's overall rate of potentially preventable readmissions, not any particular readmission. This approach recognizes that some readmissions will occur, and focuses instead on the hospital's casemix-adjusted PPR rate in comparison with an appropriate norm.

13. Why should my hospital be blamed if a readmission results from the fact that the patient or the physician in the community did not comply with the follow-up instructions?

The purpose of the analysis is not to assign blame but rather to inform hospitals about possible quality issues stemming either from inpatient care or from the transfer of care from the hospital to the community. As a primary component in the health care system of each community, hospitals can help reduce readmission rates and improve quality throughout the continuum of care.

14. Why is the number of Medicaid stays reported in Section 4 different from the number of Medicaid stays in my hospital's database?

There are several possible reasons. Most importantly, several types of patients and stays are categorically excluded from the report, for reasons discussed in Sections 1.2 and 1.4. The largest of these categories are newborns, undocumented aliens, and stays in August 2009 that were not part of a readmission chain that started in the September-July period. In addition, a small number of cases had to be excluded because of data issues. The Excel PPR report being provided to each hospital shows the specific claims that were excluded from analysis for each hospital. On a statewide basis, the reasons for excluding claims are shown in appendix Table A.2.1.

15. What are the consequences of having a high PPR rate? Will payment be affected?

A high PPR rate is an indication of opportunities to improve the quality of patient care, and in particular, the management of the discharge process and the transition to caregivers in the community. Other payers, notably Medicare, Maryland, and New York Medicaid, have pay-for-quality programs in place or planned under which a portion of payments would depend on PPR performance. At this time, no such decision has been made in Texas.

16. Will the Office of Inspector General or other agencies investigate hospitals based on these results?

Various state and federal agencies oversee the quality of care provided by hospitals, physicians and other providers. TMHP is not aware of specific oversight efforts planned as a result of this analysis.

17. What can a hospital do to reduce its PPR rate?

Many organizations and individual hospitals are working on this question. Some useful resources include:

- Health Research and Educational Trust, *Health Care Leader Action Guide to Reduce Avoidable Readmissions* (Chicago: HRET, 2010), available at www.hret.org/care/projects/guide-to-reduce-readmissions.shtml

- Jenny Minott, *Reducing Hospital Readmissions* (Washington, DC: AcademyHealth, 2008), available at www.academyhealth.org/files/publications/Reducing_Hospital_Readmissions.pdf

- The Care Transitions program aims to reduce readmissions in the Medicare program. Fourteen Medicare quality improvement organizations run pilot projects, including the

Texas Medical Foundation in Harlingen. For information, go to www.qualitynet.org and follow the link to “Hospital—inpatient” then “Readmission Measures.”

18. Will these results for my hospital be reported publicly?

No. Per statute (HB 1218), TMHP is providing hospital-specific information only to the specific hospital. The statute also states that each hospital must share the information with providers at its facility.

19. How can I get my hospital’s report?

Each hospital can pull its own report from its existing secure mailbox on the Texas Medicaid and Healthcare Partnership web page at www.tmhp.com. To minimize the risk of inadvertent disclosure, reports are not being mailed or otherwise “pushed” to hospitals.

20. What information is contained in the confidential hospital reports?

Section 4 of this report, which is not included in the public version of this report, includes hospital-specific data in the same format as Tables 2.1.1, 2.2.1, 2.3.1 and 2.4.1. In addition, each hospital will receive an Excel file that includes detailed information on the claims included and excluded from the analysis.

21. Will there be support or training on how to understand these reports and use them for improvement?

Yes. Informational meetings are scheduled as follows:

- **Dallas:** Wednesday, January 19, 2011, 9:00-11:00, Texas Scottish Rite Hospital, 2222 Wellborn St., Dallas 75219

- **Houston:** Thursday, January 20, 2011, 9:00-11:00, MHMRA of Harris County, Conference Room B, 7011 Southwest Freeway, Houston 77074

- **Mission:** Friday, January 21, 2011, 9:00-11:00, Mission Regional Hospital, 900 S. Bryan Road, Mission 78572

- **San Antonio:** Monday, January 23, 2011, 9:00-11:00, Santa Rosa Healthcare Corporation, 333 N. Santa Rosa St., San Antonio 78207

- **Amarillo:** Tuesday, January 24, 2011, 9:00-11:00, Northwest Texas Healthcare System, 1501 S. Coulter St., Amarillo 79106

To get more information about the seminars or to register, please contact Rima Mehra at 512-506-3704 or send an email to PPR.Report@tmhp.com.

22. What else can I do to get my questions answered?

The PPR methodology itself is well-described in the *PPR Classification System Definitions Manual,* available to Texas hospitals by contacting Gregg Perfetto at gmperfetto@mmm.com. Questions about the methodology and results in this report may be directed to the Texas Medicaid and Healthcare Partnership at PPR.Report@tmhp.com.

23. Are there plans for additional analysis or reporting in future years?

Yes. The PPR analysis will be repeated next year, using SFY 2010 data. The statutory requirement for a program to provide PPR information will not expire then, but specific plans for the future have not been made.

Appendix: Methodology

Note: This methodological appendix supplements the information contained in Section 1 of the main report.

A.1 Data Sources

The analysis combined fee-for-service (FFS), primary care case management (PCCM), and managed care claims.

Criteria for selecting stays were as follows:

- Hospital inpatient claim
- First date of service in state fiscal year 2009 (September 1, 2008 to August 31, 2009)
- Date paid by February 28, 2010, for FFS/PCCM claims and August 5, 2010, for managed care encounter claims
- Paid claims only
- For claims that were adjusted, the final adjusted claim only
- Include both Texas and out-of-state hospitals
- Exclude Medicare crossover claims (where Medicaid is the secondary payer behind Medicare)

The FFS and PCCM claims were from the 2009 Blue Ribbon File (BRF), which is created by TMHP each year using adjudicated claims data from the Texas Medicaid Management Information System (MMIS). The BRF, which is used for ratesetting purposes under the current payment method, reflects well-established procedures for validating, organizing, and presenting the data. The annual file is typically shared with the hospital associations, with appropriate safeguards in place regarding protected health information.

The dataset of managed care encounter claims was created especially for this analysis from the Vision 21 data warehouse. Nationwide, managed care encounter datasets tend to require more validation than fee-for-service datasets, partly because the data come to Medicaid from multiple managed care organizations and partly because the data receive less editing than do the FFS claims directly paid by Medicaid.

Once the FFS and managed care datasets were received, the next step was to validate the data and create an analytical dataset that would be used for all subsequent analysis.

A.2 Data Validation

For purposes of studying readmissions, four aspects of data quality are paramount.

- Is there a one-to-one correspondence between an inpatient stay in the real world and a record in the analytical dataset?
- Is each patient uniquely identified?
- Is each hospital uniquely identified?
- Are diagnoses and procedures (which inform PPR assignment and are used to adjust for differences in casemix among hospitals) adequately reported?

Table A.2.1
Reconciliation of Record Counts

Adjustment	Adjustment Category	Ref.	FFS/PCCM Claims	Encounter Claims	Total Claims
Records received		**A.1**	**484,995**	**245,418**	**730,413**
Not inpatient bill type	Not unique inpatient stay	A.2.1.1	0	15,121	15,121
Anomaly re crosswalk from National Provider Identifier to Texas Provider Identifier	Data issue	A.2.3.2	0	1,388	1,388
Discharge date anomaly	Data issue	A.2.1.3	524	0	524
Unreliable discharge status—single MCO	Data issue	A.2.5.1	0	15,861	15,861
Unreliable discharge status—other	Data issue	A.2.5.1	48	1,140	1,188
Duplicate claim	Not unique inpatient stay	A.2.1.2	17	5,411	5,428
Consolidated within claim chains	Not unique inpatient stay	A.2.1.3	33	1,290	1,323
Undocumented aliens	Study design	A.2.2.2	83,624	0	83,624
Newborns	Study design	A.5.1	141,355	63,433	204,788
APR-DRG grouping errors	Data issue	A.3.3	429	874	1,303
PPR grouping errors	Data issue	A.5.5	632	425	1,057
PPR exclusions and non-events	Study design	A.5.2	21,425	2,882	24,307
August 2009, not a readmission	Study design	A.5.4	18,495	11,783	30,278
Analytical dataset			**218,413**	**125,810**	**344,223**
Subtotal—not unique inpatient stay			*50*	*21,822*	*21,872*
Subtotal—study design			*264,899*	*78,098*	*342,997*
Subtotal—data issue			*1,633*	*19,688*	*21,321*

Notes

1. Claims could be excluded from the analytical dataset for more than one reason. Record counts for each exclusion reason therefore would differ depending on the order in which the validation steps were performed.
2. The count of records excluded from August 2009 reflects a 15-day PPR window. See Section A.5.4.

Table A.2.1 shows a reconciliation of record counts, starting from the datasets received and ending with the analytical dataset. From an initial total of 730,413 records received, 21,872 were excluded because they did not uniquely represent a hospital inpatient stay. Another 342,997 records were excluded by design of the study, for example because they were for newborns or undocumented aliens. Of the remaining 365,544 records, another 21,321 records, or 5.8%, were excluded due to various data issues. TMHP expects the prevalence of data issues to be lower in future years due to continual improvements in the datasets. The analytical dataset used for the PPR analysis comprised 344,223 claims.

Table A.2.2 shows counts of the dataset records affected by various adjustments as described in the following sections.

A.2.1 Defining Complete Hospital Stays

The goal was to ensure a one-to-one match between an inpatient hospital stay in the real world and a record in the analytical dataset.

A.2.1.1 Validating Bill Types

Bill type is a three-digit field submitted by the hospital to the payer.[19] A value of 111, for example, is a single admit-through-discharge claim at a hospital for inpatient care. All received values of bill type were examined, resulting in the exclusion of 15,121 managed care claims that were not for hospital inpatient stays.

A.2.1.2 Apparent Duplicate Claims

Seventeen FFS/PCCM claims and 5,411 managed care claims were excluded because they appeared to be duplicates of other records in the dataset. Exact duplicates were defined as showing identical values for patient, hospital, admission date, discharge date, discharge status, bill type, and billed charges. Potential duplicates were defined as showing identical values for all of the above criteria except billed charges. The existence of duplicate records does not necessarily imply duplicate payments to hospitals, but it does mean that the duplicated records need to be excluded from the analytical dataset in order to prevent double-counting.

Table A.2.2
Adjustments to Analytical Dataset Claim Values

Adjustment	Ref.	Fee for Service Claims	Encounter Claims	Total Claims
Anchor claim in a claim chain	A.2.1.3	28	370	398
Frequency in bill type set to 1	A.2.5.2	880	-	880
At least one diagnosis code reformatted and/or corrected	A.2.4.2	67	2	69
At least one procedure code reformatted and/or corrected	A.2.4.2	130,576	54,883	185,459

Notes

1) Only claims within the analytical dataset of 344,223 claims are shown in this table.

2) Some claims may be counted in more than one line in this table.

A.2.1.3 Claim Chaining

Hospitals may submit more than one claim for a single inpatient stay, for three reasons.

- ***Adjustments.*** An earlier claim may be corrected ("adjusted") by a later claim. In this case, the claims processing system includes the original claim, a reversal of the original claim, and the new, adjusted claim. The criteria used to select the FFS and managed care dataset specified that only the final adjusted claim should be included (Section A.1).

- ***Interim claims.*** A hospital may submit an interim claim (indicated by bill frequency 2 or 3 and discharge status 30) while a patient remains in the hospital. When the patient is discharged, the hospital submits a final claim with bill frequency 4 and the appropriate discharge status. (Bill frequency is the third digit in the bill type field.)

- ***Late charges.*** A hospital may submit a supplementary claim for late charges without adjusting the original claim. A claim for late charges shows bill frequency 5. This can be confusing because the claims processing system then contains two valid claims for the same patient with the same dates of service.

TMHP examined all situations where there were claims with overlapping dates of service for the same patient in the same hospital. Claims where there was a one-day difference (e.g., one claim with last date of service Monday and another claim with first date of service Tuesday) were also examined. For situations where there was a one-day difference, TMHP relied on admit date, bill type and discharge status to determine whether the claim represented a single stay or an initial admission followed by a readmission.

"Claim chaining" is the process of combining multiple claims for a single stay into a single record in the analytical dataset. It applies to both interim claims and late charges and can reveal anomalies with adjusted claims. When all claims are billed as expected, claim chaining can be done systematically using a simple algorithm. Anomalies do occur, however, including internal inconsistencies (e.g., the bill frequency indicates an interim claim but the discharge status shows the patient was discharged home) and situations where there appear to be missing claims in the chain.

The Blue Ribbon File received for this study had already been processed through claim chaining while the managed care encounter file had not. Both files were checked for potential claim-chaining situations and then the claim-chaining algorithm was applied. Situations not handled by the algorithm were reviewed on an individual basis. In most cases an examination of the admit dates, bill types, discharge statuses, dates of service, diagnoses and other data allowed determination of the claim status with a high degree of confidence. A total of 1,721 claims were chained into 398 stays. To prevent double-counting, the other 1,323 claims were excluded from the analytical dataset (Table A.2.1). Table A.2.2 shows that data values for the 398 "anchor" claims were adjusted to reflect the entire stay. In the Blue Ribbon File, the 33 claims chained into 28 stays were all situations involving late charges.

A.2.1.4 Discharge Date Anomalies

A total of 524 FFS claims were excluded because the claims did not clearly show the discharge date. These anomalies can occur because the client lost Medicaid eligibility during the stay, because the client was still a patient when Blue Ribbon File was created, or because of billing errors by the hospital.

A.2.1.5 Same-Day Stays

After claim chaining, there were 2,488 stays where the patient was admitted and discharged on the same calendar day. (These stays do not include patients who were transferred between acute-care hospitals.) These stays were examined to ensure that they were not outpatient claims. Same-day stays may occur because the patient died, left against medical advice, or needed only a limited amount of inpatient care. TMHP examined the bill type, billed charges, diagnoses and procedures. No obvious patterns were found that would cause exclusion of any of these stays from the analytical dataset.

A.2.1.6 Claims with Low Charges

Hospital care is very expensive: on average, Texas hospitals charge over $6,000 for a day of inpatient care.[20] Therefore, all claims with charges under $500 a day were examined to look for anomalies in total charges or in the length of stay. TMHP's concern was that the claim may not represent a complete inpatient stay or the length of stay may have been wrong.

This validation step was performed after the above steps. No situations were found where the claim should be excluded because of an obvious anomaly. Most of the claims with low charges were for psychiatric care, and average charges per day were usually close to the $500 threshold.

A.2.2 Unique Identification of Patients

A.2.2.1 Patient Identifier

Patients were uniquely identified using their Texas Medicaid client identification number, which is required from hospitals on both FFS and managed care claims. In general the quality of this data field was excellent. There were some claims where a newborn baby had the same client number as the mother, but these situations did not affect the record counts because all newborns were excluded from the analytical dataset. Identification of PPRs was done using the patient identifier, hospital identifier and dates of service as key fields. If a patient changed managed care plans, or moved between the FFS/PCCM and managed care sectors, then the PPR count reflected the patient's Medicaid eligibility during the initial stay.

A.2.2.2 Undocumented Aliens

Medicaid pays for inpatient care received by undocumented aliens in certain emergency circumstances. These claims were excluded from the analysis because the patients are not eligible for Medicaid on a continuing basis. Therefore, any readmissions likely would not show up in the MMIS. There were 83,624 FFS claims excluded for this reason. The vast majority were for childbirth.

A.2.3 Unique Identification of Hospitals

A.2.3.1 Fee for Service

In the Blue Ribbon File of fee-for-service and primary care case management stays, hospitals are uniquely identified by the Texas Provider Identifier (TPI) in the MMIS. Each TPI comprises a seven-digit base ID and a two-digit suffix. For example, 12346701 might be a hospital's TPI for the hospital itself while 123456702 might be the ambulatory surgical center at the same hospital. It is not uncommon for a single hospital to have multiple TPIs. The Blue Ribbon File consistently shows the appropriate TPI for inpatient hospital care, in large part because the TPI matters in calculating payment on claims. Each TPI is associated with a provider name and a provider specialty, e.g., “hospital, non-profit, acute, 1-50 beds.”

A.2.3.2 Managed Care

The managed care plans do not use the TPI in claims adjudication and do not transmit it to the Texas Medicaid data warehouse. Instead, they transmit the National Provider Identifier (NPI). For purposes of this study, the NPI was mapped to a TPI based on the NPI and supplementary data received from the MCO, such as type of bill, provider taxonomy code, tax ID, provider address, and benefit code. For 1,388 claims, a TPI could not be assigned to an NPI with a high degree of confidence, and these claims were omitted from subsequent analysis.

A.2.4 Diagnosis and Procedure Coding

A.2.4.1 Importance of Coding

Rates of readmission depend not only on the reason for the initial admission but also on the severity of the patient’s condition during the initial admission. To be fair in comparing hospitals it is therefore necessary to have accurate data on the patient’s clinical condition. This was measured using All Patient Refined Diagnosis Related Groups (APR-DRGs), as discussed in Section A.3. APR-DRGs depend critically on the diagnosis and procedure codes listed by the hospital on the claim and then stored in the payer’s claims processing system. Diagnosis and procedure coding on claims is never perfect, but it is essential to check these data fields for major issues that could invalidate comparisons among hospitals.

A.2.4.2 Valid Values

ICD-9-CM diagnosis and procedure code values can take different formats. For example, diagnosis codes can be three, four or five digits, including leading or trailing zeroes, with a decimal place implied after three digits for most codes but after four digits for “E” codes. Similar potential for confusion exists with the procedure codes. The data as received had multiple formats, which were standardized for analysis. In particular, almost all claims had procedure codes listed with a leading zero, so that a four-digit procedure code was received as five digits.

Other anomalies can arise when a hospital submits a diagnosis code or procedure code that is not valid for the date of discharge. These anomalies typically arise near October 1 of each year, which is the nationwide revision date for the ICD-9-CM codeset. In cases where it was obvious from the code used what the appropriate code should have been, the code value was adjusted, usually by adding or deleting a fifth digit to a diagnosis code.

Only 69 claims required adjustment to at least one diagnosis code. A total of 185,459 claims required adjustment to at least one procedure code, but in almost all cases the adjustment was simply to delete a leading zero.

A.2.4.3 Coding Completeness

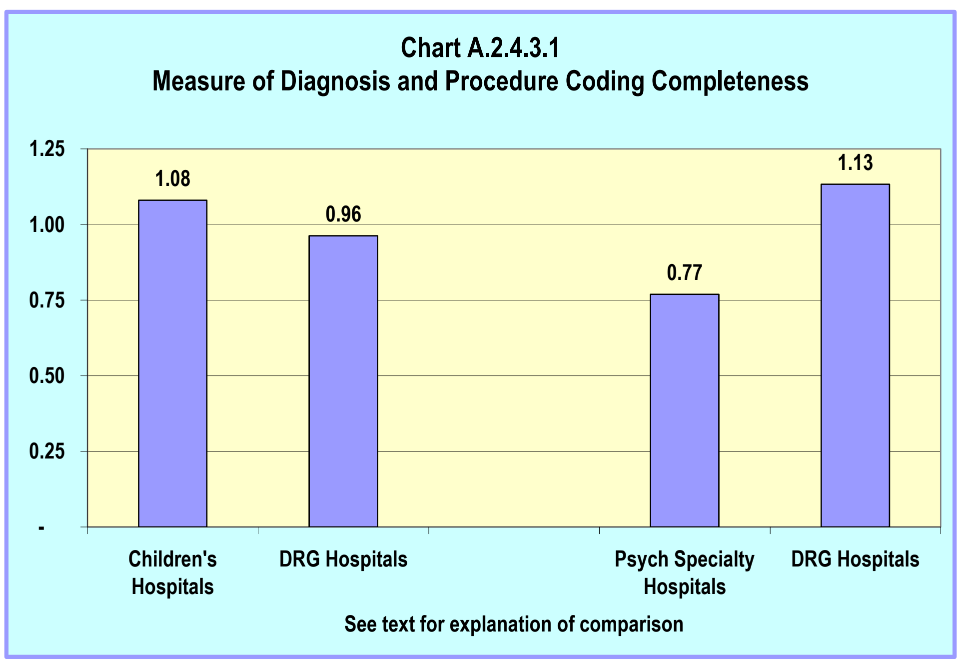
Within the FFS and PCCM sectors, Texas Medicaid pays general hospitals based on MS-DRGs. These hospitals have strong financial incentives to be thorough in including diagnosis and procedure codes on claims, since these codes drive the DRG assignment for the claim. Medicaid pays other hospitals on cost reimbursement principles using “TEFRA” standards, which is a reference to the federal Tax Equity and Fiscal Responsibility Act of 1982. The two main categories of TEFRA hospitals are children’s hospitals and psychiatric specialty hospitals. Without the financial incentive of DRG payment, the concern is that diagnosis and procedure codes would be under-reported by children's and specialty psychiatric hospitals. A similar concern occurs on the managed care side, where DRG-style payment methods that reward complete coding are believed to be rarely used in calculating payment for children's and specialty psychiatric hospitals.

One measure of coding completeness is simply the average number of diagnosis and procedure codes per claim. This measure is useful if casemix is very similar between DRG hospitals and TEFRA hospitals. A more careful approach would be to adjust for the number of secondary diagnoses and procedures, which varies with the types of patients seen. TMHP therefore did a casemix-adjusted comparison, making use of the fact that every claim shows a principal diagnosis. The principal diagnosis typically drives the assignment of the *base* APR-DRG.[21] (In some cases, the principal operating room procedure drives the DRG assignment.) The average count of secondary diagnoses and procedures for each base APR-DRG was calculated and used as a norm to compare DRG and TEFRA hospitals.[22] The children's hospitals were compared with pediatric stays at the general hospitals while the specialty psychiatric hospitals were compared with psychiatric stays at the general hospitals.

The results, as shown in Chart A.2.4.3.1, suggested that the children's hospitals tended to have *more* complete coding than the general hospitals. The children's hospitals reported an average of 4.75 diagnosis and procedure codes per claim. Based on the mix of base APR-DRGs at these hospitals, an average of 4.39 codes would have been expected. The ratio of actual to expected code counts per claim was therefore 1.08. For general hospitals treating pediatric patients, the actual number of codes was 3.98 but the expected number was 4.13, so the actual/expected ratio was 0.96. Although it remains possible that even more diagnosis and procedure codes *should* have been reported at the children's hospitals, the chart implies that there is no obvious deficit in coding in the children's hospitals relative to the general hospitals.

Specialty psychiatric hospitals reported many fewer diagnosis and procedure codes than would be expected given their mix of base DRGs. On average, specialty psychiatric hospitals reported 2.33 codes per claim, whereas 3.03 would be expected. General hospitals reported 4.86 codes per claim, or 13% more than the 4.29 codes that would be expected. It was also noteworthy that 4.86 codes per claim at the general hospitals was more than twice as many codes as the 2.33 average at the specialty hospitals. The differences in both absolute terms and relative to expectations suggest that coding is relatively incomplete in the specialty hospitals.

When coding is incomplete, the average casemix of patients can be understated. That, in turn, would understate the expected rates of PPR, resulting in reported PPR performance ratios that are worse than they may be in reality. If there is a bias (where "bias" in used in the statistical sense), then its magnitude cannot be determined without better data



from these hospitals. The magnitude may be modest, however, because Table 2.5.1 showed that the likelihood of PPRs increased only modestly as severity of illness increased for the most common mental health DRGs.

A.2.5 Other Data Validation Steps

A.2.5.1 Discharge Status

In the discharge status field, the hospital indicates whether the patient went home, died, left against medical advice, was transferred to another hospital, was transferred to another setting (such as a nursing home), or is still in the same hospital. For PPR analysis, this field is essential. Patients who died, who left the hospital against medical advice, or who were transferred to another acute-care hospital are excluded from the PPR analysis.

In general, data in this field were in line with expectations. The chief exception was that one managed care plan showed about 50% of its claims with a discharge status of 30 (still a patient) while every other claim showed a discharge status of 01 (discharged home). It is highly unlikely that half of all claims would be interim claims and that the dataset would include literally no patients who died, were transferred or left against medical advice. Because this important field was suspect, all 15,861 claims from this plan were excluded from the dataset.

Another 48 fee-for-service claims and 1,140 managed care claims were excluded due to various other issues with regard to discharge status. Most commonly, the discharge status was 30 but there was no subsequent claim.

A.2.5.2 Bill Type

As described in Section A.2.1.1, one purpose of the bill type field is to identify interim claims. For example, three claims for a single stay might show bill types 112 (first interim claim), 113 (continuing interim claim) and 114 (final interim claim). When the Blue Ribbon File is created, the claim chaining process shows the chained claim as having the bill type associated with the first claim in the chain, 112 in this example. In the analytical dataset these values were changed to 111 to show that the record now represents a complete admit-through-discharge claim.

A.3 Grouping by APR-DRG

A.3.1 Overview

APR-DRGs are one of the DRG algorithms used to classify inpatients according to their clinical characteristics. After the Medicare Severity Diagnosis Related Group (MS-DRG) algorithm used by Medicare, the APR-DRG algorithm is probably the most widely known DRG algorithm. While Medicare DRGs were designed for use only in the Medicare population, APR-DRGs were designed for an all-patient population. In particular, APR-DRGs were designed to be more appropriate than Medicare DRGs for pediatrics, obstetrics, and various conditions that are not common in a Medicare population. APR-DRGs have been found to be suitable for a Medicaid population and are increasingly being used by Medicaid programs to calculate payment.[23]

APR-DRGs were developed by 3M Health Information Systems and the National Association of Children's Hospitals and Related Institutions.

A.3.2 Base DRG and the Severity of Illness

An advantage of APR-DRGs for analysis such as the present study is that the algorithm has a straightforward, easily understandable structure. Each APR-DRG is in the format 123-4. The first three digits represent the base DRG, which can be thought of as the reason for admission (usually the principal diagnosis, sometimes the principal operating room procedure). The fourth digit represents the severity of illness on an ordinal scale of 1 to 4. Each inpatient stay is assigned to a single APR-DRG in an 18-step process that is documented in the APR-DRG definitions manual available from 3M Health Information Systems.

The PPR software includes logic to assign a stay to an APR-DRG. This assignment is identical to what stand-alone APR-DRG software would do, with two exceptions. First, some tracheostomy stays are re-assigned from the tracheostomy APR-DRG to an APR-DRG that reflects the underlying condition (e.g., stroke or pneumonia). Second, eight APR-DRGs have been split into two. The split allows the PPR logic to differentiate more finely between readmissions that were likely planned (e.g., cardiac catheterization following an initial admission for cardiac ischemia) and those that were likely unplanned (e.g., cardiac catheterization with a diagnosis of acute ischemia).

Version 28 of the combined APR-DRG and PPR software package was used for this analysis. Although this version was released in November 2010, it can be appropriately used for claims with earlier dates of service.

A.3.3 Validation of APR-DRG Assignments

About 0.3% of stays in the analytical dataset grouped to an error DRG, either "ungroupable" or the principal diagnosis code listed was not appropriate as a principal diagnosis. This percentage is in line with similar experience elsewhere.

There are three base APR-DRGs for situations where the principal diagnosis is not consistent with procedures performed. Given the wide range of care provided in modern hospitals, there can be perfectly valid reasons for such mismatches. These claims were examined for any obvious data issues. This examination found several examples of formatting problems in the procedure code fields. These were fixed and the APR-DRG algorithm was run again.

A.4 Medicaid Care Category

Medicaid Care Category is a categorization algorithm developed by TMHP for purposes of this analysis. It is intended to result to a manageable list of categories (about ten) that are aligned with both the policy areas of a typical Medicaid program and the internal organization of a typical hospital. Table 1.1.1 shows the number of stays in the analytical dataset in each care category for the FFS/PCCM and managed care populations. Pediatrics are defined as 17 years of age or younger; the categories of medical, surgical, etc. are defined by the APR-DRG; and patients in the obstetric category may be of any age. In purpose, MCCs are similar to Major Diagnostic Categories (MDCs), which are based on DRGs and used by many hospital researchers. For purposes of an analysis such as this one, the chief drawback of the MDC categorization is that it does not split out pediatric stays. The number of MCCs is also easier to work with the number of MDCs (25).

A.5 PPR Analysis

A.5.1 Overview

The PPR methodology developed by 3M Health Information Systems is separate and quite distinct from other methods of measuring readmissions. Refer to Chapter 1 for further information on the PPR methodology. The logic for defining PPRs is well documented in R.F. Averill et al., *Potentially Preventable Readmissions Classification System: Definitions Manual* (Wallingford, CT: 3M Health Information Systems, 2010). The 3M methodology has been used in the Florida and Maryland all-patient populations and the New York Medicaid population.[24]

A.5.2 Time Frame

A "PPR chain" is created when more than one readmission follows an initial admission. For example, a two-day stay on January 1 followed by a two-day readmission on January 10 followed by another two-day readmission on January 20 constitutes a single PPR chain. To count in a chain, each readmission must be within the PPR window (e.g., 15 days) of the discharge date in the previous stay. In this example, the third stay counts in the PPR chain because it occurred within 15 days of the second stay, even though more than 15 days had passed since the discharge from the first stay.

Although the analytical dataset comprises 12 months of data, the PPR results are based only on 11 months of data. That is, for admissions in the September-July period TMHP looked for readmissions in the September-August period. The use of a one-month "run-out" period minimizes the likelihood that readmissions were omitted from the analytical dataset. An example of such an omission would be if a patient were admitted on July 31, discharged on August 20, and then readmitted on September 1. Similarly, if a patient were admitted in July, readmitted in August and readmitted again in September, then the PPR results would count the readmission chain accurately but miss the second readmission in the count of total readmissions.

A.5.3 PPR Grouping Errors

About 0.3% of stays in the analytical dataset were excluded because the PPR software could not assign it as an initial stay or a readmission, for example because the patient was shown as being in two hospitals on the same day.

A.6 Casemix Adjustment of PPR Rates by Hospital

A.6.1 Overview

Differences among hospitals and other patient groupings (e.g., health care delivery method) were accounted for using the method of indirect standardization. Indirect standardization involves comparing an actual rate for a group of patients with an expected rate that is based on the characteristics of the group being assessed (e.g., age, type of illness) applied to rates observed in a larger population having the same characteristics. This is commonly expressed as the ratio of the actual rate to the expected ratio, called the actual-to-expected (AE) ratio. Section A.6.2 describes how expected values were developed.

The numbers reported describe actual PPR rates for Texas Medicaid patients in SFY 2009. There is no statistical uncertainty. It is natural to generalize from experience in a single year, using it as a basis for predicting future experience. Such generalization effectively treats the 2009 experience as a sample of some larger reality. If the results are used in this way it is important to keep in mind that the results are subject to natural, random variation. This is particularly important when assessing the rates of small hospitals, or small sub-sets of patients (e.g., care categories) within a hospital. The report has two features to assist hospitals in accounting for this variation. First, actual/expected ratios are reported only for patient groupings that meet a minimum volume test, which is discussed in Section A.6.3. Second, for each AE ratio that is reported TMHP performed a statistical test of the likelihood that the actual rate observed would occur in a group of the same size and composition drawn at random from among all Texas Medicaid inpatients in SFY 2009. This test is discussed in Section A.6.4.

A.6.2 Development of Expected Rates

Expected rates were based on the PPR experience of all Texas Medicaid patients in SFY 2009. Four important characteristics that are strongly correlated with the incidence of PPRs were taken into account:

- ***APR-DRG:*** The principal condition for which the patient was treated and important procedures performed, as categorized by the 3M software (see Section A.3.2).

- ***Severity of illness (SOI):*** A four-level scale based on all conditions for which the patient was treated, as categorized by the 3M software (see Section A.3.2).

- ***Age:*** Pediatric (17 years of age and younger) or adult (18 and over).

- ***MH/SA co-morbidity:*** For medical-surgical stays, whether or not the patient had a serious mental health or substance abuse condition as a comorbidity. (A MH/SA comorbidity is not strongly correlated with PPR rate when the initial admission is MH/SA or obstetrics.)

For each combination of APR-DRG, severity of illness and age, the observed statewide PPR rate was established as the norm, except for obstetrics, for which no distinction by age was made. The first three columns of Table A.6.2.1 illustrate these norms. The MH/SA co-morbidity characteristic was accounted for as an adjustment to the norm, for medical/surgical stays only (not MH/SA or obstetrics). Table 2.5.2 documents the factors used.

Each initial admission was assigned an expected PPR rate, which is (i) the norm for the applicable APR-DRG, SOI and age combination, times (ii) the applicable MH/SA adjustment factor. The expected rate for an individual initial admission represents the estimated probability that it would be followed by a PPR. For a group of initial admissions (patients) the sum of these estimated probabilities is the expected number of readmission chains, and the average is the expected PPR rate. The last three columns of Table A.6.2.1 illustrate this process for a group of 10 patients.

A.6.3 Minimum Volume Test

For very low volumes, the AE ratio is subject to large swings resulting from random events and should not be reported or tested for significance. Table A.6.3.1 shows several scenarios. The first case is a group of 40 admissions drawn at random from the patients with a single combination of APR-DRG, severity of illness, and age combination where the statewide PPR rate is 5%. A chance difference of 1 readmission from the expected changes the AE ratio by 50%, from 1.0 to 0.5 in the case of reduction or 1.0 to 1.5 in the case of an increase. There are no intermediate possibilities; it is impossible for this group to have an AE ratio of 0.9 or 1.1.

The second and third examples show how the expected rate also can affect the degree of volatility in the AE ratio. This is why number of readmissions is part of the test.

Table A.6.2.1
Illustration of Norm Development and Calculation of Expected Values

Patient Characteristics				Norms		
APR-DRG		Age (Category)	Has MH/SA Co-morbidity?	Average Statewide PPR Rate (a)	MH/SA Adjustment Factor (b)	Estimated Probability of a PPR(a) x (b)
053-2	Seizure	32 (Adult)	Yes	5.9%	1.133	6.7%
053-2	Seizure	15 (Pedi.)	No	3.6%	0.990	3.6%
139-3	Other pneumonia	51 (Adult)	No	7.5%	0.977	7.3%
139-3	Other pneumonia	4 (Pedi.)	Yes	4.9%	1.463	7.2%
247-1	Intestinal obstruction	43 (Adult)	No	7.9%	0.977	7.7%
247-1	Intestinal obstruction	8 (Pedi.)	No	2.6%	0.990	2.6%
540-3	Cesarean delivery	23 (All)	Yes	3.0%	1.000	3.0%
540-3	Cesarean delivery	17 (All)	No	3.0%	1.000	3.0%
751-1	Major depression	26 (Adult)	No	9.7%	1.000	9.7%
751-1	Major depression	16 (Pedi.)	Yes	8.7%	1.000	8.7%
				Expected PPR Rate		**5.9%**
				Expected Number of PPRs		**0.59**

Since it is useful for hospitals to know what happened to small groups and to be able to contrast that with the overall statewide experience for similar patients, the report includes actual and expected values in all cases. To discourage over-interpretation of the relationship, the report includes the AE ratio only if three conditions are met: (1) the group has at least 40 cases, (2) there are at least 5 actual readmissions, and (3) the number of expected readmissions is at least 5. These particular levels follow precedent established by Maryland and Florida.

Table A.6.3.1
Scenarios Illustrating Fluctuation of AE Ratio When Volume Is Low

Group Size	Expected		Actual			AE Ratio
	Rate	# PPRs	# PPRs	PPR Rate	Prob.	
Example 1						
40	5%	2	1	2.5%	27%	0.50
			2	5.0%	28%	1.00
			3	7.5%	19%	1.50
Example 2						
50	2%	1	0	0.0%	36%	0.00
			1	2.0%	37%	1.00
			2	4.0%	19%	2.00
Example 3						
50	8%	4	2	4.0%	14%	0.50
			3	6.0%	20%	0.75
			4	8.0%	20%	1.00
			5	10.0%	16%	1.25
			6	12.0%	11%	1.50

A.6.4 Statistical Test of Significance

Significance of hospital-specific actual/expected rates was tested using the Cochran-Mantel-Haenszel (CMH) test of conditional independence.[25] The CMH statistic is an estimate of how likely it would be for a hospital's AE ratio to be 1.00 in reality yet for the observed difference from 1.00 to be as wide as it is. Other things equal, the CMH statistic is higher when the number of stays is large and/or the observed AE ratio is further away from 1.00. For the CMH statistics in this study, the thresholds are 2.7055 at the 90% confidence level and 3.8415 at the 95% confidence level. Because the study compares 230 hospitals using a 10% confidence level, 23 hospitals would be expected to show statistically significant differences from zero due to simply to chance. A description of the application of the CMH test to indirectly standardized PPR rates can be found in the methodology documentation provided by the Florida Agency for Health Care Administration (reported at www.floridahealthfinder.gov).[26]

Notes

[1] §531.913 at www.legis.state.tx.us/billlookup/text.aspx?LegSess=81R&Bill=HB1218

[2] Results in this analysis were produced using data obtained through the use of proprietary computer software created, owned and licensed by the 3M Company. All copyrights in and to the 3M™ Software are owned by 3M. All rights reserved.

[3] In methodology and scope, this study is similar to the Florida study. Refer to www.floridahealthfinder.gov/Researchers/Reference/Methodology/Methodology.aspx#hreadmit and Norbert I. Goldfield, Elizabeth C. McCullough, John S. Hughes et al., "Identifying Potentially Preventable Readmissions," *Health Care Financing Review,* 30:1 (Fall 2008), pp. 75-91.

[4] In 2008, net patient revenue (both inpatient and outpatient) for the Texas hospital industry was $39.1 billion. The comparable figure for 2009 is not yet available. American Hospital Association, *Hospital Statistics 2010* (Chicago: AHA, 2010), p. 137. The comparison of discharges takes into account the exclusion of normal newborns in the AHA definition of a discharge.

[5] Refer to Texas Health and Human Services Commission, *Hospital Services Handbook* (Austin: HHSC, 2010), p. HS-9.

[6] In a few cases, Medicaid acts as the primary payer when dually eligible clients exhaust or are ineligible for the Medicare inpatient hospital benefit. These stays are included in the analytical dataset used for this report.

[7] Gerard F. Anderson and Earl P. Steinberg, "Hospital Readmissions in the Medicare Population," *New England Journal of Medicine,* 311:21 (Nov. 22, 1984), pp. 1349-1353.

[8] Institute of Medicine, *To Err Is Human* (Washington, DC: IOM, 1999); Donald M. Berwick, *Escape Fire: Designs for the Future of Health Care* (San Francisco: Jossey Bass, 2004).

[9] Guy L. Clifton, *Flatlined: Resuscitating American Medicine* (New Brunswick, NJ: Rutgers University Press, 2009), p. xi.

[10] Refer to Question 17 in Chapter 3.

[11] These may be sent to Gregg Perfetto at gmperfetto@mmm.com.

[12] Much of the methodology presented in this section and Section 1.6 is based on the methodology used in Florida. Refer to the references above.

[13] Alan Agresti, *Categorical Data Analysis,* second edition (Hoboken, NJ: John Wiley & Sons, 2002).

[14] The $104 million figure is for initial admissions in the 11-month period from September 2008 through July 2009. From Table 1.1.1, total Medicaid payments for the 12-month fiscal year were $3.3 billion. Adjusting for the difference in time periods yields the result of 3.5%.

[15] Stephen F. Jencks, Mark V. Williams and Eric A. Coleman, "Rehospitalizations among Patients in the Medicare Fee-for-Service Program," *New England Journal of Medicine,* 360:14 (April 2, 2009), pp. 1418-1428.

[16] Because the study includes multiple comparisons among hospitals, the reader should bear in mind that about 10% of the hospitals would show a statistically significant difference from 1.00 simply because of random variation.

[17] Kevin Quinn and Connie Courts, *Sound Practices in Medicaid Payment for Hospital Care* (Hamilton, NJ: Center for Health Care Strategies, 2010).

[18] Kevin Quinn, "New Directions in Medicaid Payment for Hospital Care," *Health Affairs* 27:1 (January/February 2008), pp. 269-280.

[19] Strictly speaking, the bill type field comprises four digits, including a leading zero. TMHP follows convention in referring only to the three meaningful digits. Refer to Ingenix Inc., *Uniform Billing Editor* (Salt Lake City, UT: Ingenix, August 2010), pp. II-12 to II-109.

[20] The figure includes all patients (including Medicare, Medicaid, commercial payers and uninsured) but excludes newborn days.

[21] Using the full APR-DRG—base plus severity of illness—would be circular reasoning. Assignment of the severity of illness depends in part on the number of secondary diagnoses on a claim. The principal diagnosis, by contrast, must be present on every claim. An operating room procedure would also be typically sufficiently important to be coded on almost any claim.

[22] This analytic technique is known as indirect rate standardization.

[23] Quinn, "New Directions"; Quinn and Courts, *Sound Practices,* pp. 6-7.

[24] For more information on the Florida analysis, refer to Goldfield et al., "Identifying Potentially Preventable Readmissions."

[25] Agresti, *Categorical Data Analysis.*

[26] Refer to www.floridahealthfinder.gov/Researchers/Reference/Methodology/Methodology.aspx#hreadmit.