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DOI: 10.1377/hlthaff.2024.00596
HEALTH AFFAIRS 43, NO. 12 (2024): 1619–1627

Upcoding Linked To Up To Two-Thirds Of Growth In Highest-Intensity Hospital Discharges In 5 States, 2011–19

ABSTRACT Diagnosis-based payment systems can create incentives to upcode patients to a higher level of severity to increase payment. In some instances, upcoding can be a form of fraud if providers code patients to a higher complexity than is appropriate, whereas in other instances, upcoding can accurately reflect patient acuity. We estimated the increase in Medicare Severity Diagnosis-Related Group (MS-DRG) upcoding during the period 2011–19, using all-payer discharge-level data from five states. During this period, the number of discharges with the highest MS-DRG coding intensity increased by 41 percent. Adjusting for changes in patient characteristics, length-of-stay, and hospital characteristics, we estimated that the increase would have been 13 percent in the absence of changes in coding behavior. We estimated that in 2019, the increase in upcoding (relative to 2011 coding practices) was associated with $14.6 billion in hospital payments, including $5.8 billion from private health plans, $4.6 billion from Medicare, and $1.8 billion from Medicaid. These findings can contribute to the growing body of evidence supporting the design of payment models that limit distortions in payment and resource allocation.

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As a way to control costs, traditional Medicare has used the inpatient prospective payment system (IPPS) to pay for hospital inpatient stays since 1983.[1] The IPPS assigns each stay to a diagnosis-related group (DRG) on the basis of principal diagnosis and the presence of complications and comorbidities. At this time, the IPPS uses an expanded set of DRGs introduced in 2007, called Medicare Severity Diagnosis-Related Groups (MS-DRGs), which allow for more variation in payment associated with patient complexity than previous sets of DRGs.

This payment system creates incentives for hospitals to upcode patients to a higher level of complexity. Following previous academic studies, we define *upcoding* as coding practices to systematically document patients to a higher severity level.[2–4] In some situations, upcoding can be a form of fraud if providers code patients to a higher complexity than is appropriate, whereas in others, upcoding can accurately reflect patient acuity. Fraudulent coding is clearly problematic,[5] but even upcoding that does not cross the line into fraud can result in payment inefficiencies—for example, if it results in an MS-DRG having a healthier and less resource intensive mix of patients than anticipated when a payer set payment rates.

Studies that focused on major changes to the IPPS attribute large amounts of excess hospital spending to upcoding,[2,3] but there is little evidence on the magnitude of MS-DRG upcoding or its impacts on costs since 2010.[6] The Office of Inspector General (OIG) of the Department of Health and Human Services warned in 2021 that upcoding appears to have increased between 2014 and 2019, based on the observation that the proportion of traditional Medicare hospital stays coded into the highest MS-DRG complication and comorbidity category increased while average length-of-stay remained flat.[7]

Given that factors other than upcoding, such as changes in patient composition, could account for these patterns, a more rigorous analysis is needed to draw conclusions about the extent and spending impacts of upcoding. MS-DRG upcoding has also not been examined carefully outside of traditional Medicare, even though other payers often base payments on MS-DRGs or use other DRG-based systems.[8–13] In addition, upcoding may vary across payers because of differences in payment rates or payer scrutiny. For example, private insurance prices were roughly 240 percent of Medicare prices as of 2019,[14] so the financial incentive to upcode a hospital stay for a privately insured patient may be greater than for a Medicare patient.

To address these issues, we estimated the extent of MS-DRG upcoding and its impact on hospital spending during the period 2011–19, using all-payer discharge-level data from five states.[15] We adapted a method recently developed by Vivian Ho and colleagues to quantify changes in upcoding over time while adjusting for changes in case-mix and patient demographics.[16]

Study Data And Methods

MEDICARE SEVERITY DIAGNOSIS-RELATED GROUPS Under the IPPS, hospitals receive higher payments for more complex patients.[1] As of federal fiscal year 2019, each of the 761 MS-DRGs was associated with one of 335 base MS-DRGs.[17] Most base MS-DRGs have multiple MS-DRGs (up to three) to assign stays to different patient severity levels. A base MS-DRG with three MS-DRGs delineates between stays for patients with major complications and comorbidities (MCC, the highest level of severity), with complications and comorbidities (CC), or without either MCC or CC (the lowest level of severity). The severity levels for base MS-DRGs with two levels are as follows: first, with MCC and without MCC, and second, with MCC or CC and without MCC or CC. Each of these MS-DRG levels is assigned a payment weight that reflects its average resource use among traditional Medicare patients, with larger weights given to higher severity levels.[1] The payment weight reflects the resource intensity used during a patient's stay and is used to calculate the IPPS payment to the hospital.

DATA We obtained State Inpatient Databases prepared by the Healthcare Cost and Utilization Project for Florida, Kentucky, New York, Washington State, and Wisconsin for calendar years 2010 through 2019.[15] Data from Wisconsin were available only in 2011 and later years. Each State Inpatient Database includes all discharge records from community hospitals (including academic hospitals) for its given state and year. These data include approximately 15 percent of all US community-based hospitals and nearly 20 percent of discharges nationwide.[18]

Our analysis excluded MS-DRGs with only one level of severity, those that were introduced or discontinued during the study period, and those affected by introductions or discontinuations. We excluded discharges at critical access hospitals, which traditional Medicare reimburses on a cost basis rather than the IPPS. We excluded discharges in which the patient died (approximately 2 percent of discharges) because of concern that the inclusion of patients who died with a short length-of-stay would confound the relationship between length-of-stay and MS-DRG complexity. We also excluded discharges of patients who were older than age 110 or who had missing data on length-of-stay, payer, or patient demographics. Our analytic sample included 37,942,945 discharges for 239 base MS-DRGs at 553 hospitals. Further details and summary statistics are in online technical appendix section 1.[19]

We used the Elixhauser Comorbidity Indices, thirty-day readmission index, to control for patient health status at admission.[20] The index sums weights indicative of risk associated with specific preexisting conditions. Conditions included in the Elixhauser readmission index have limited overlap with those included as MS-DRG complications and comorbidities. See technical appendix section 2 for discussion of the use of the Elixhauser readmission index in our analysis.[19]

ANALYSIS To estimate how upcoding changed between fiscal years 2011 and 2019, we modeled the probability that discharges were coded at the highest severity level within each base MS-DRG. For each year, we measured the increase in upcoding relative to the status quo in the earliest period (2011) as the difference in the observed number of discharges with the highest severity level and a predicted number.

Our method, which was adapted from Ho and colleagues' recent analysis of emergency department upcoding,[16] used linear regression to predict coding at the highest severity level, based on observable characteristics of the hospital stay, the hospital, and the patient. Explanatory variables included patient characteristics (age, sex, and race and ethnicity), payer, preadmission health, length-of-stay, and hospital fixed effects. A separate model was estimated for each base

We found that two-thirds of the observed growth in complex MS-DRGs between 2011 and 2019 was potentially due to upcoding.

MS-DRG, allowing estimated parameters to vary across base MS-DRGs. The model was estimated in a base year, and then predictions were constructed by applying the parameters of the base year model to the sample of discharges in each subsequent year.

As a result of the transition to the International Statistical Classification of Diseases and Related Health Problems, Tenth Revision (ICD-10), starting in 2016, we used 2011 as the base year for 2012–15 and 2016 as the base year for 2017–19. To estimate the increase in upcoding (relative to 2011 coding behavior) for years after the ICD-10 transition, we assumed that the rate of upcoding would remain constant between 2015 and 2016 (since we lacked a baseline year for 2016). We then calculated predictions in 2017 and later years by adding the 2017 and 2019 predicted discharges to the predicted amount for 2016, scaled by the change in total discharges.

We aggregated predicted discharges at the highest intensity across base MS-DRGs and payers to estimate increases in upcoding, overall and by payer. We calculated 95% confidence intervals using a hospital-clustered bootstrap with 100 resamples. Technical appendix section 3 contains further detail regarding the regression specifications, prediction calculations, and bootstrapping approach.[19]

To understand the effect of upcoding on payment, we estimated the increase in MS-DRG payment weights. We calculated the change in weights for each base MS-DRG as the increase in upcoding multiplied by the weight for the MS-DRG with the highest intensity minus the weight for the MS-DRG with the second-highest intensity. We then divided the increase in weights by the sum of the observed weights (inclusive of discharges not in the analytic sample) to approximate the percentage increase in payment associated with upcoding.

We also calculated changes in the frequency of specific secondary diagnoses, providing insight into which complications and comorbidities drove our estimated increases in upcoding. We only examined diagnosis codes after the ICD-10 transition because previous codes are no longer used.

SENSITIVITY ANALYSIS We were concerned that technological change and quality improvement could bias our results if either resulted in shorter stays over time. To address this concern, we estimated a model that allowed the effect of length-of-stay to vary by a hospital's technological level and quality. We obtained American Hospital Association Annual Survey data to create measures of technological level: an index for advanced imaging equipment, an indicator for conducting major organ transplants, and an indicator for furnishing advanced cardiac care.[21–24] To measure hospital quality, we used thirty-day readmission rates for heart failure, acute myocardial infarction, and pneumonia from the Centers for Medicare and Medicaid Services (CMS) Hospital Readmissions Reduction Program.[25] We also estimated a model in which each year of the study used the prior year as its baseline, therefore allowing us to predict upcoding based on parameter estimates from the preceding year, rather than estimates based on data up to four years before. Last, we were concerned that using the Elixhauser thirty-day readmission index would be less predictive of complex discharges compared with the Elixhauser in-hospital mortality index; therefore, we estimated a model that used the in-hospital mortality index.

LIMITATIONS We acknowledge several limitations. We used a broad definition of *upcoding* that did not allow us to distinguish between changes in coding practices to accurately capture severity and fraudulent coding.[2–4,6] Federal agencies and some academic studies limit their definition of *upcoding* to include only fraud.[5,26,27]

This study examined upcoding as the change in discharges coded at the highest severity level. Other forms of upcoding that were not examined are possible and may be quantitatively important—for example, upcoding into a different base MS-DRG or classifying observation stays as inpatient admissions.

Our model measured the changes in upcoding using discharge data. Although we controlled for patient demographics and health at the time of admission, we could not control for all factors of patient health, such as factors that are only accessible through electronic health records or chart data. It is plausible that some of the increase in upcoding was attributable to discharges having more complicated patients over time. For this reason, we view our estimate as an upper bound on the increase in MS-DRG upcoding. Furthermore, as we lacked clinical data, we were unable to determine which specific discharges were upcoded.

The study included discharges from only five states, which may limit the generalizability of our findings. Some state policies such as all-payer rating setting or the use of global budgets may limit the incentive to upcode.

Study Results

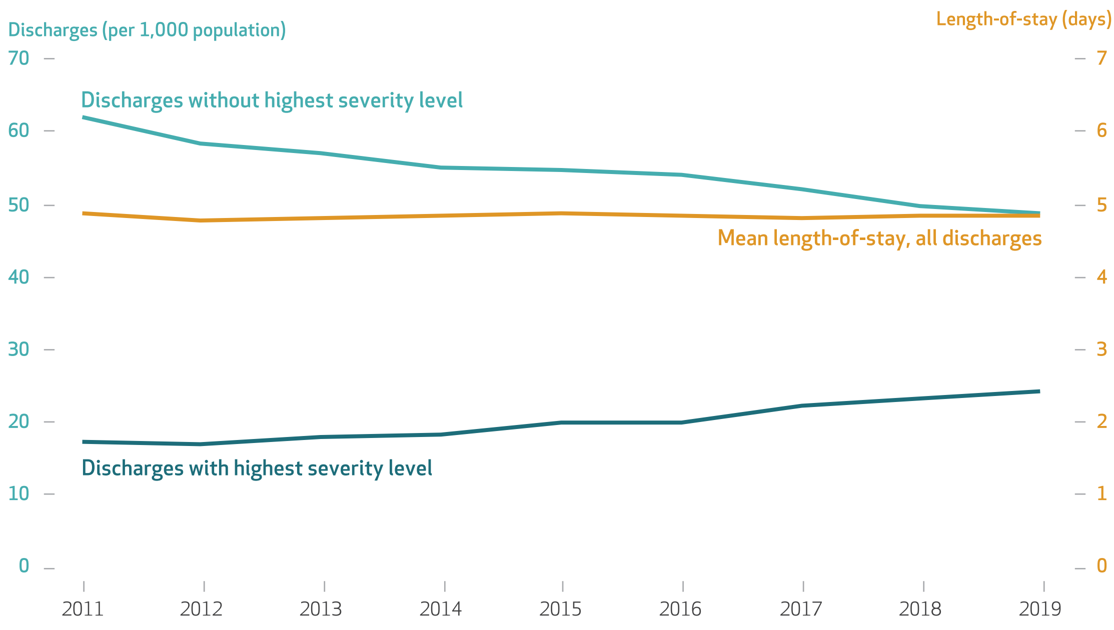
The number of all-payer discharges with the highest MS-DRG severity level increased from 17.2 per 1,000 population in 2011 to 24.2 per 1,000 population in 2019 (for the 239 base MS-DRGs included in the analysis), which is a 41 percent increase (exhibit 1).[28] The average length-of-stay among discharges at any severity level ("all discharges" in exhibit 1) remained nearly identical, at 4.9 days. Although we could not compare patient health at the time of admission across the entire study because of the transition to ICD-10, the average Elixhauser thirty-day readmission index increased by 14 percent between 2011 and 2015 and by 19 percent between 2016 and 2019 (data not shown).

After controlling for patient composition, length-of-stay, and hospital fixed effects, we estimated that the number of discharges per 1,000 population with the highest intensity would have grown from 17.2 to 19.4 (95% CI: 18.9, 19.9), which is a 13 percent increase between 2011 and 2019 (exhibit 2). This result implies that in 2019, roughly two-thirds of the increase was unexplained by our model. The unexplained portion of the increase represents an upper bound on the increase in upcoded discharges relative to the base period of 2011. As a percentage of discharges in the analytic sample, an additional 6.6 percent (95% CI: 6.4, 6.7) of discharges among all payers were upcoded in 2019, relative to the base period of 2011 (exhibit 3). We found an increase in upcoding in all five states, with the smallest increase seen in New York (3.6 percent; 95% CI: 3.4, 3.7) and the largest increase in Washington State (14.5 percent; 95% CI: 14.1, 15.1) (appendix exhibit A).[19]

The base MS-DRG with the largest increase in upcoding, in terms of number of upcoded dis-

EXHIBIT 1

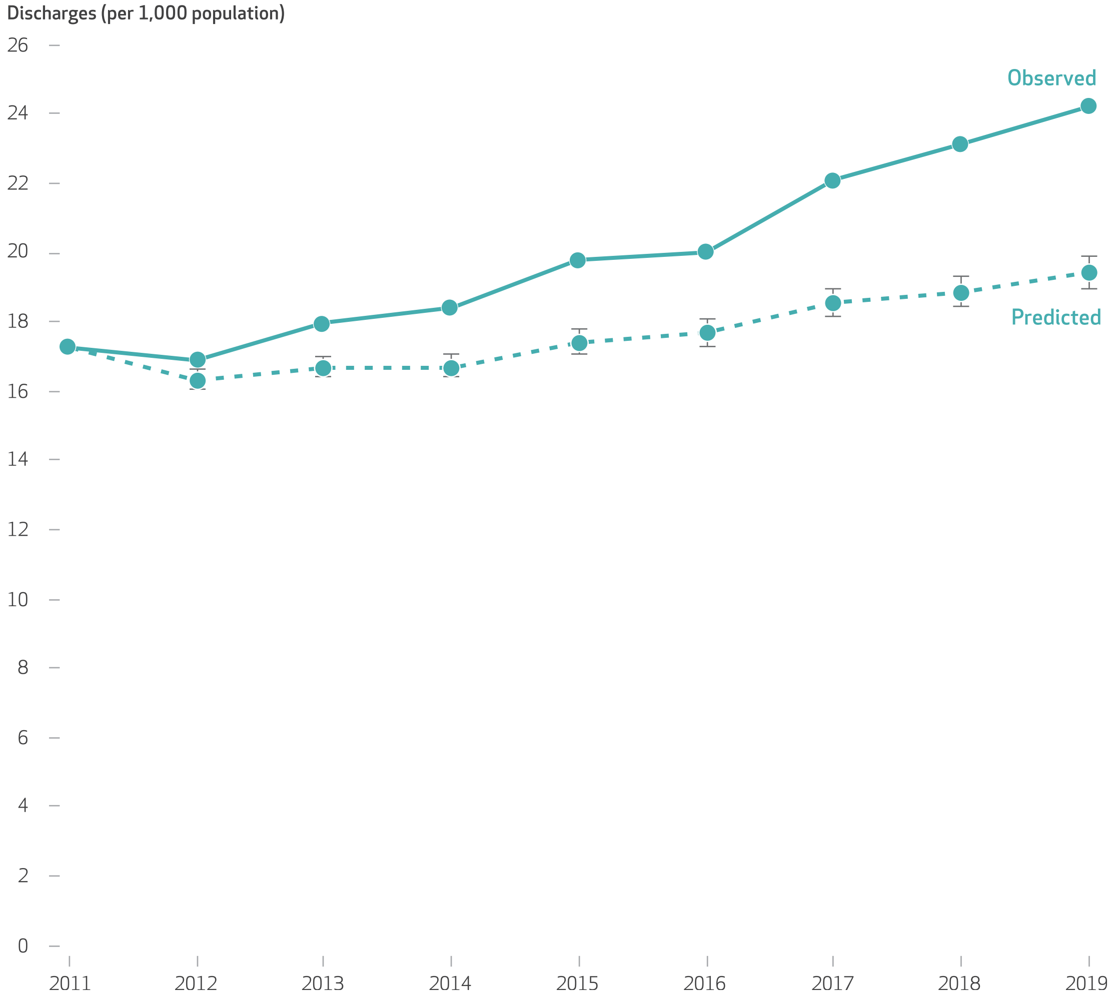
Hospital discharges in 5 states, by Medicare Severity Diagnosis-Related Group (MS-DRG) severity level and length-of-stay, 2011–19



SOURCE Authors' analysis of data from the 2011–19 Healthcare Cost and Utilization Project all-payer State Inpatient Databases for Florida, Kentucky, New York, Washington State, and Wisconsin. **NOTES** The darker teal line shows discharges coded at the highest severity level ("major complications and comorbidities" or "major complications and comorbidities/complications and comorbidities") for 239 base MS-DRGs that have severity levels within the base MS-DRG, of 335–340 total base MS-DRGs, dependent on the year. The lighter teal line shows discharges coded for base MS-DRGs that do not have the highest severity level ("without major complications and comorbidities" or "without complications and comorbidities"). The orange line shows lengths-of-stay for discharges for MS-DRGs with any severity level. We excluded base MS-DRGs with a single severity level or those that were added, deleted, or affected by the addition or deletion of other base MS-DRGs during the study period.

EXHIBIT 2

Observed and predicted hospital discharges with the highest Medicare Severity Diagnosis-Related Group (MS-DRG) severity level in 5 states, 2011–19



SOURCE Authors' analysis of data from the 2011–19 Healthcare Cost and Utilization Project all-payer State Inpatient Databases for Florida, Kentucky, New York, Washington State, and Wisconsin. **NOTES** Data reflect 239 base MS-DRGs that have severity levels within the base MS-DRG, of 335–340 total base MS-DRGs, dependent on the year. We excluded base MS-DRGs with a single severity level or those that were added, deleted, or affected by the addition or deletion of other base MS-DRGs during the study period. Error bars are 95% confidence intervals estimated from bootstrapping 100 replications of the analysis.

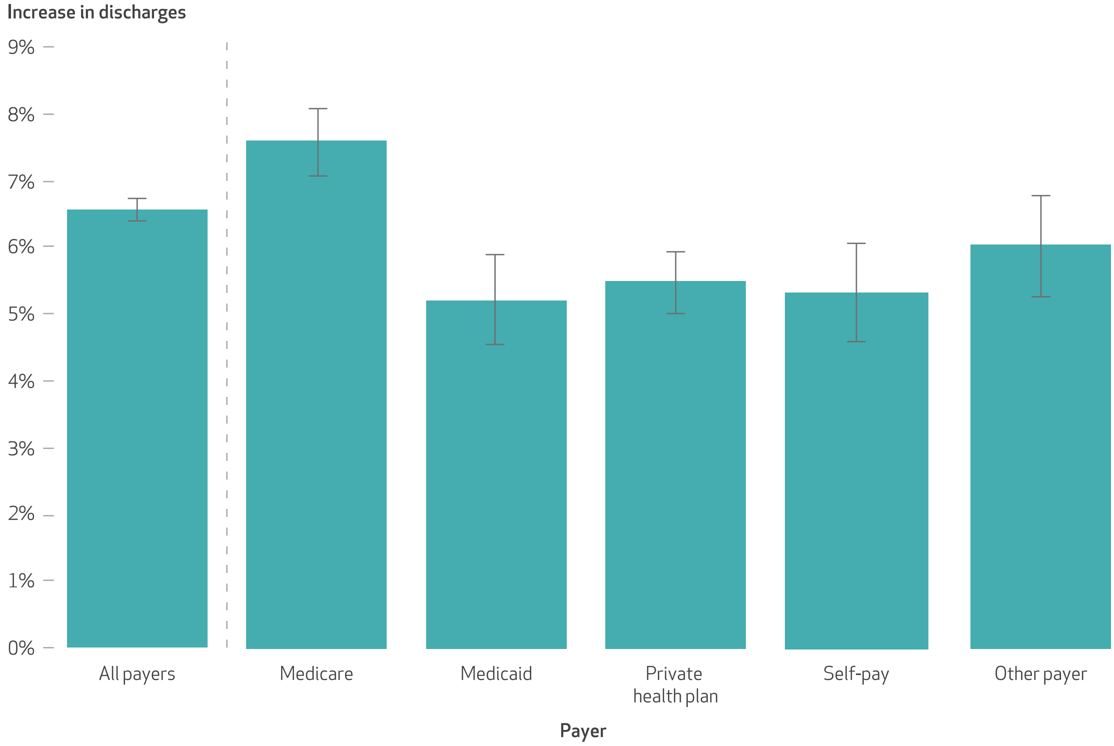
charges in 2019, was heart failure and shock, for which an additional 27.0 percent (95% CI: 25.9, 28.1) of all discharges were upcoded in 2019 compared with 2011 (appendix exhibit B).[19] Simple pneumonia and pleurisy (16.1 percent; 95% CI: 14.8, 17.4), chronic obstructive pulmonary disease (17.2 percent; 95% CI: 15.7, 18.7), septicemia or severe sepsis without mechanical ventilation for ninety-six or more hours (5.0 percent; 95% CI: 4.2, 5.8), and bronchitis and asthma (14.0 percent; 95% CI: 12.3, 15.6) completed the top five base MS-DRGs with the largest numerical increases in upcoding.

Upcoding grew more for Medicare discharges relative to other payers. In 2019, an additional 7.6 percent (95% CI: 7.1, 8.1) of Medicare discharges were upcoded relative to 2011 (exhibit 3) compared with 5.5 percent (95% CI: 5.0, 5.9) for private health plans and 5.2 percent (95% CI: 4.5, 5.9) for Medicaid.

In exhibit 4, we estimate the increase in MS-DRG payment weights (assuming that upcoding was from the second-highest intensity to the highest intensity), which approximates the percentage change in payments (inclusive of discharges not in the analytic sample, for which we assumed there was no upcoding). Overall, upcoding was associated with an increase of 1.7 percent (95% CI: 1.2, 2.1) in MS-DRG weights in 2019. For Medicare, the increase was 2.0 per-

EXHIBIT 3

Increase in upcoded hospital discharges as percent of all discharges in 5 states, by payer, 2019



SOURCE Authors' analysis of data from the 2011–19 Healthcare Cost and Utilization Project all-payer State Inpatient Databases for Florida, Kentucky, New York, Washington State, and Wisconsin. **NOTES** Data reflect 239 base Medicare Severity Diagnosis-Related Groups (MS-DRGs) that have severity levels within the base MS-DRG, of 335 total base MS-DRGs in 2019. We excluded base MS-DRGs with a single severity level or those that were added, deleted, or affected by the addition or deletion of other base MS-DRGs during the study period. We measured the increase in upcoding in 2019 relative to the status quo in 2011 as the difference between the observed and predicted number of discharges in 2019 with the highest severity level. Error bars are 95% confidence intervals estimated from bootstrapping 100 replications of the analysis.

cent (95% CI: 1.7, 2.2), which was not statistically different from the increase for private health plans (1.8 percent; 95% CI: 1.5, 2.1). For Medicaid, the increase was 1.2 percent (95% CI: 0.7, 1.6).

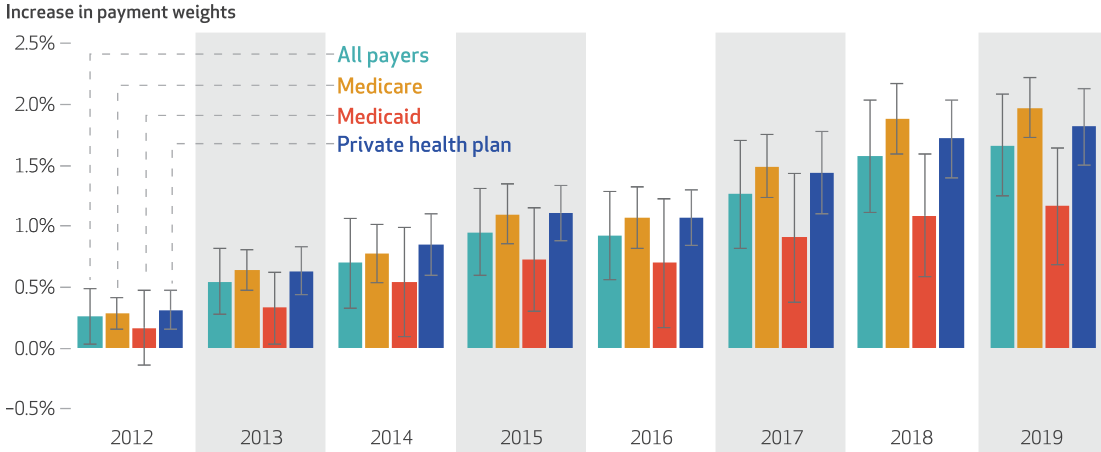
We conducted sensitivity analyses to test the robustness of our results. First, we allowed the parameter for length-of-stay to vary by the quality and technological level of the hospital (appendix exhibit C).[19] Second, for each year, we estimated the increase in upcoding using a baseline of the previous year instead of using baseline years of 2011 and 2016 (appendix exhibit D).[19] We found that neither of these models resulted in a meaningful change in our results compared with the base model. We found that using the Elixhauser in-hospital mortality index, rather than the thirty-day readmission index, resulted in a slightly higher estimate of upcoding, both overall (appendix exhibit E) and for individual base MS-DRGs (appendix exhibit F).[19]

TRENDS IN COMPLICATIONS AND COMORBIDITIES For the ten base MS-DRGs with the largest growth in upcoding in 2019 relative to 2016, measured by number of upcoded discharges in 2019, we examined secondary diagnoses that, when coded, would elevate a discharge to the highest severity level. In particular, we found relatively large growth in the use of I50 codes that specify the type of heart failure (diastolic, systolic, or both) for heart failure and shock discharges. For example, the use of code I5033 acute on chronic diastolic (congestive) heart failure increased from 2.7 percent of discharges in 2016 to 20.6 percent in 2019 for heart failure and shock discharges (appendix exhibit G presents the MS-DRG and secondary diagnosis combinations with the largest growth).[19]

We also observed relatively large increases in the frequency of J96 codes, which are used to code acute respiratory failure, for several base MS-DRGs. For example, the use of code J9601 acute respiratory failure with hypoxia was present on 9.0 percent of discharges for simple pneumonia and pleurisy in 2016 and 16.7 percent in 2019. We also found a large increase in the fre-

EXHIBIT 4

Increase in Medicare Severity Diagnosis-Related Group (MS-DRG) payment weights attributed to upcoding of hospital discharges in 5 states, by payer, 2012–19



SOURCE Authors' analysis of data from the 2011–19 Healthcare Cost and Utilization Project all-payer State Inpatient Databases for Florida, Kentucky, New York, Washington State, and Wisconsin. **NOTES** The increase in MS-DRG payment weights is expressed as a percent of the weights for all base MS-DRGs, including discharges excluded from the analytic sample, which we assumed were not upcoded. We assumed that all upcoding was from the second-highest severity level to the highest severity level. For base MS-DRGs with three severity levels, we assumed that upcoding was from "with complications and comorbidities" to "with major complications and comorbidities." For base MS-DRGs with two severity levels, we assumed that upcoding was from "without major complications and comorbidities" to "with major complications and comorbidities" or from "without complications and comorbidities" to "with complications and comorbidities," dependent on the severity levels associated with the base MS-DRG. Error bars are 95% confidence intervals estimated from bootstrapping 100 replications of the analysis.

quency of J18 codes for lobar pneumonia. For example, code J181 lobar pneumonia, unspecific organism, was present on 0.2 percent of discharges for septicemia or severe sepsis without mechanical ventilation for ninety-six or more hours in 2016 and 4.8 percent in 2019 (appendix exhibit G).[19]

Discussion

Upcoding of hospital inpatient stays is a concern to policy makers, as it leads to higher payments, either through fraud or by creating payment inefficiencies when upcoding is clinically accurate.[7,29] Using data from five states, we observed that all-payer hospital discharges coded to the highest MS-DRG severity level, for 239 base MS-DRGs, grew by 41 percent between 2011 and 2019. However, we found that only one-third of the growth in MS-DRGs with the highest severity level was explained by changes in observable discharge, patient, and hospital characteristics. Two-thirds of the growth in complex MS-DRGs was unexplained, implying an upper bound on the increase in upcoding of 4.8 discharges per 1,000 population in 2019 compared with 2011. In 2019, this increase in upcoding represented 6.6 percent of discharges among the base MS-DRGs included in the study.

We estimated that in 2019, MS-DRG payment weights were approximately 1.7 percent higher when we assumed that all upcoding was from the second-highest to the highest coding intensity. Using National Health Expenditure data from CMS, we estimated that the increase in MS-DRG payment weights was associated with $14.6 billion in payments in 2019, including $5.8 billion from private health plans and $4.6 billion from Medicare.[30] See technical appendix section 4 for discussion of the calculations of these estimates.[19]

For understanding of the total influence of MS-DRG upcoding on payment, our estimates should be considered in addition to payments associated with upcoding that existed by 2011. Amanda Cook and Susan Averett estimated that the introduction of MS-DRGs in 2007 was associated with a 3 percent increase in MS-DRG payment weights.[2] If we assume that this estimate represented all MS-DRG upcoding in 2011, then our analysis implies that payments associated with upcoding grew to $40.6 billion in 2019, representing 1.1 percent of all US health care payments. For Medicare, payments associated with upcoding would have been $11.6 billion in 2019, which is comparable to the Medicare Payment Advisory Commission's finding that payments associated with the upcoding of health risk scores by Medicare Advantage plans was $11 billion in 2019.[31]

Further research is needed to increase understanding of the proportion of upcoding that represents fraudulent coding practices versus accurate and more complete coding. Keith Joiner and colleagues estimated that fraudulent upcoding detected by CMS's Comprehensive Error Rate Testing in Medicare Part A was roughly $650 million per year during the period 2010–19,[27] which would imply that fraudulent activities make up a minority of MS-DRG upcoding.

There are several plausible reasons why upcoding increased during the study period. First, revisions to the IPPS might have created new opportunities for hospitals to upcode. CMS introduced MS-DRGs in 2007, and although other research reported an increase in upcoding after their implementation,[2] hospitals may have continued to adapt and learn how to effectively code complexity, much in the same way that Medicare Advantage plans have increased the coding intensity of health risk scores over time.[31] Second, one study suggested that hospitals responded to the introduction of ICD-10 coding guidelines by coding certain secondary diagnoses less conservatively.[32] For example, a 2017 guidance issued by CMS and the National Center for Health Statistics provided guidelines on how to use I50 codes to specify the type of heart failure.[33] Third, the percentage of hospitals using certified electronic health records increased from 28 percent in 2011 to 96 percent in 2019.[34] Previous studies documented that electronic health records are associated with an increase in diagnoses and complexity, although their impact on upcoding is unclear.[35,36] Fourth, private prices for hospital services were increasing over the course of the study period.[37,38] This price growth could have increased the incentive to upcode private-payer hospital stays. Although the increase in upcoding was largest for Medicare when measured as a percentage of discharges, the percentage increase in payment weights associated with upcoding was similar between Medicare and private health plans, which could be due to hospitals focusing their upcoding efforts on a set of more expensive MS-DRGs.

Conclusion

Investigating upcoding in all-payer hospital discharges, we found that two-thirds of the observed growth in complex MS-DRGs between 2011 and 2019 was potentially due to upcoding, as the increase was not explained by changes in observable discharge, patient, or hospital characteristics. The results of these analyses can support efforts to curb upcoding and its impact on payments. The study also contributes to the growing body of evidence supporting the design of payment models that limit distortions in payment and resource allocation. ■

This research was funded through the National Institute for Health Care Reform. The authors thank the following for their input on this study: Melony Sorbero, Amanda Cook, Paul Koegel, Christine Eibner, and Peter Hussey. To access the authors' disclosures, click on the Details tab of the article online.

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