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Quantifying Productivity Growth in the Delivery of Important Episodes of Care within the Medicare Program Using Insurance Claims and Administrative Data

John A. Romley, Abe Dunn, Dana Goldman, and Neeraj Sood

11.1 Introduction

Multifactor productivity (MFP) growth is the ultimate source of gains in living standards, and growth appears to have slowed in the United States since the turn of the century (Byrne, Oliner, and Sichel 2013; Fernald 2015). One view of the current situation is that the technological progress of earlier eras is unlikely to be matched in the future, notwithstanding the ongoing information revolution and foreseeable developments (Gordon 2016). An alternative view is that government economic statistics have systematically mismeasured MFP improvement, in fact understating it (Feldstein 2017).

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Recent assessments cast some doubt on this alternative view as a convincing account of the apparent slowdown in productivity growth (Byrne, Fernald, and Reinsdorf 2016; Syverson 2017).

These assessments, while informative, have not squarely addressed the issue of productivity growth in health care. This sector accounted for 17.9 percent of GDP in 2017 (Martin et al. 2018). As health spending has grown, so have better treatments become available (Newhouse 1992). Quality change is a well-known challenge for measuring prices, and the mismeasurement of health care inflation was a key concern of the Boskin Commission (Boskin et al. 1998). Indeed, taking account of improved outcomes, the price of heart attack treatment has actually declined markedly over time (Cutler et al. 1998).

With respect to MFP, there is a longstanding hypothesis that health care and other services suffer from a "cost disease," by which a comparatively meager flow of labor-saving efficiencies drives production costs higher and higher (Baumol and Bowen 1965; Baumol et al. 2012; Newhouse 1992). The Medicare Board of Trustees has adopted this position in its long-term financial projections, through an assumption that MFP within the health care sector will grow more slowly than MFP outside of health care (OASDI Board of Trustees 2018). More starkly, the Bureau of Labor Statistics (BLS) has estimated that hospitals and nursing and residential care facilities experienced negative MFP growth from 1987 through 2006 (Harper et al. 2010). If productivity is truly declining in our health care system, efforts to contain cost, improve quality, or both, become even more difficult.

While the BLS measures MFP by applying a rigorous and consistent framework across industries, it is plausible that its measurement framework does not adequately reflect quality change in health care[1] (Cylus and Dickensheets 2007; Groshen et al. 2017; Matsumoto 2019). Another challenge in this context is that production is joint between the firm and the consumer in the sense that patients present themselves to providers for care with good, bad, or middling health. Providers who face sicker patients may use more (or fewer) resources in treatment. In a prior study, we found that US hospitals substantially improved their productivity from 2002 through 2011, but only after we accounted for trends in patient severity and treatment outcomes. Improvement in patient outcomes was largely responsible (Romley, Goldman, and Sood 2015).

Yet the treatment of heart attacks and other conditions does not end with discharge from the hospital. We need to understand productivity in the treatment of complete episodes of care, including, for example, rehab services and follow-up doctor visits. Even if individual providers are pro-

1. Similarly, the National Income and Product Accounts and the Centers for Medicare and Medicaid Services both track *spending* on health care without adjustment for quality (Sensenig and Wilcox 2001).

ductive, there is widespread concern about poor coordination of care, due to problems of information and incentives across providers (Davis 2007). Accordingly, public and private decision makers are assessing and paying with respect to performance on episodes of care.[2] For example, the Centers for Medicare and Medicaid Services (CMS) recently expanded its innovation portfolio to include a Bundled Payments for Care Improvement Advanced Model (Centers for Medicare and Medicaid Services 2019a).

While the complexity of health care makes productivity assessment challenging, at the same time there are voluminous data to work with. In this study, we use insurance claims and administrative data to quantify trends in the productivity of treatment of acute episodes of care among elderly Americans. Specifically, we assess a wide range of important conditions and procedures over a reasonably long timeframe (in the last year studied, 2014, the total cost of providing these episodes is estimated to be $38 billion, measured in 2014 dollars). To our knowledge, this is the first study that analyzes productivity change in delivering acute episodes, including services received after the initial hospital stay.

Previewing our key findings, productivity improved for a majority of the episode types studied, in some cases at an annualized rate in excess of 1 percent. For the episode types that experienced productivity improvement, patient outcomes also improved, sometimes substantially.

11.2 Approach

The starting point for our analysis is CMS's Inpatient Files (Research Data Assistance Center 2019). Our version of the Inpatient Files includes a random 20 percent sample of Medicare beneficiaries. As table 11.1 shows, there were 29,841,183 stays at 6,353 short-term acute-care hospitals over the period 2002–2014. The Inpatient File is actually a claim-level file, and multiple claims may be associated with the same stay. While the Medicare Provider Analysis and Review File reports at the stay level, we use the Inpatient File in order to implement a complex algorithm developed by CMS for the purpose of identifying unplanned hospital readmissions (Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation (YNHHSC/CORE) 2014). Appendix figure 11A.1 provides an overview of the CMS algorithm. Publicly available code produces a stay-level dataset by combining associated claims.

One of the episode types we study is acute myocardial infarction (AMI), or heart attack. Table 11.1 shows that 811,517 stays at 5,510 hospitals were

2. There is general agreement among experts that *price* measures in the health care sector should focus on the entire episode of care, rather than the prices of individual service inputs (National Research Council 2010; World Health Organization 2011). Researchers at the BLS and the Bureau of Economic Analysis have recently focused on price measurement based on an episode of care.

Table 11.1 **Sample construction for AMI (heart attack) episodes**

Stays/episodes	Beneficiaries	Hospitals	Description
29,841,183	7,880,612	6,353	All Medicare FFS stays in short-term acute-care hospitals, 2002–2014, based on random 20% sample of beneficiaries
811,517	635,380	5,510	Heart attack (acute myocardial infarction, i.e., AMI) stays
798,414	625,301	5,505	Excluding stays in fourth quarter of 2014 (incomplete follow up as index stays)
558,999	501,940	5,290	Stays/episodes meeting CMS readmission measure criteria
476,892	432,606	4,852	Excluding episodes with any missing cost-to-charge ratios
463,770	421,133	4,769	Episodes meeting AHRQ IQI risk measure criteria
461,830	419,531	4,739	Excluding index hospital-years with no Census sociodemographic data available
413,636	376,129	3,869	Excluding index hospital-years that did not match to teaching status (residents per bed) data in CMS Impact Files
402,778	366,645	3,560	Excluding index hospital-years with a zero rate for any favorable health outcome

for patients with a principal diagnosis of AMI. The first three digits of these diagnoses were *410*, per the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9) (National Center for Health Statistics). The other episodes include congestive heart failure, pneumonia, gastrointestinal hemorrhage ("GI bleed"), hip fracture, stroke, "lower extremity" joint (hip and knee) replacement (LEJR), and chronic obstructive pulmonary disease (COPD). These episodes are also identified on the basis of validated ICD-9 (diagnosis and procedure) codes (Agency for Healthcare Research and Quality 2019).

We define episodes of care as beginning with admission to a short-term acute-care hospital and ending either 90 days after discharge from the initial (i.e., "index") stay or with death, whichever came first. CMS's hospital-based bundled-payment models have almost invariably used 90-day post-discharge windows (Centers for Medicare and Medicaid Services 2017). Because we do not have access to Medicare service utilization in 2015, we exclude episodes that started in the fourth quarter of 2014 (see table 11.1). Death dates are available from the research-identifiable version of CMS's Beneficiary Summary Files (specifically, the A/B segments that report Medicare enrollment and other beneficiary attributes). We treat a beneficiary as having died only if her reported date was flagged as having been validated by the Social Security Administration or Railroad Retirement Board. Under our Data Use Agreement, our CMS data also include uniquely encrypted beneficiary identifiers; these IDs are used to link the Beneficiary Summary Files to the Inpatient Files (and other claims files noted below).

To quantify productivity in delivering episodes of care, we estimate the following relationship for each episode type:

$$\ln(Y_{ht}/C_{ht}) = \alpha + \boldsymbol{S}_{ht}\beta_S + \boldsymbol{O}_{ht}\boldsymbol{\beta}_O + g(t) + \varepsilon_{ht},$$

in which Y_{ht} is the total output of episodes initiated with an admission to index hospital h during year t, C_{ht} is the total cost (including post-discharge care) of providing these episodes, $\boldsymbol{S}_{ht}$ is severity factors for the patients in these episodes, and $\boldsymbol{O}_{ht}$ is other elements of hospital production. The left-hand side of this equation is the ratio of output to inputs, or more colloquially "bang for the buck." This metric is commonly used in economic assessments of health system performance (Gu et al. 2019; Romley, Goldman, and Sood 2015; Romley et al. 2019; Sheiner and Malinovskaya 2016).

On the right-hand side of the equation, our object of interest is the function $g(t)$, a common-across-hospitals but year-specific residual between measured determinants of production and measured output. As is standard, we will interpret this residual as MFP and changes in the residual over time as productivity improvement (or decline). As is well understood, the validity of this interpretation depends on the validity of the measurement of production determinants and output.

We measure output in each index hospital-year based on the quantity as well as quality of episodes. Under this framework, the health care system receives less credit (in terms of output) for a relatively low-quality episode yet is still responsible for the cost of scarce resources in delivering the episode. In prior studies, we have defined output as the *number* of inpatient stays that met a quality threshold explained below (Romley, Goldman, and Sood 2015; Romley et al. 2019). While this definition has a natural interpretation, its implication is that the elasticity of substitution between quantity and quality is equal to −1. Evidence on the trade-off between quantity and quality in health care is remarkably scarce. Grieco and McDevitt (2016) recently investigated the provision of kidney dialysis services, and their findings imply an elasticity of quantity with respect to quality of −1.4, which is an estimate consistent with higher quality being costly to produce.[3] We apply this estimate as our baseline value, while also considering our previously used value.

In prior studies, we defined quality by a composite rate of favorable health outcomes. For hospitals, we used survival for at least 30 days beyond the admission, and avoidance of an unplanned readmission within 30 days

3. Grieco and McDevitt (2016) report a semi-elasticity of quality with respect to quantity of −0.016 percent, where quality is measured based on the rate of infection. To obtain the elasticity of quality with respect to quantity, we multiply this value with the mean success rate of no infections of 87.5 percent calculated from the paper to obtain an estimated elasticity of −1.4.

of discharge. Both these outcomes correspond to quality-of-care metrics publicly reported by CMS and used in Medicare hospital reimbursement (Centers for Medicare and Medicaid Services 2019c; Centers for Medicare and Medicaid Services 2019e; Centers for Medicare and Medicaid Services 2019f). Specifically, mortality has been a metric for six of the episode types we study (LEJR and COPD are the exceptions), while readmission has been a metric for all our episode types. In this study, we continue to use these outcomes. For example, as table 11.1 reports, 558,999 AMI stays at 5,290 hospitals met all the inclusion/exclusion requirements of the CMS readmission algorithm.

Some potential episodes were inconsistent with the algorithm because the corresponding admission was a readmission that occurred within an episode already in progress.[4] In addition, patients must have been 65 years old or older at admission and continuously enrolled in "traditional" fee-for-service Medicare (Parts A and B) to be included, and a candidate index stay is excluded if the patient was discharged "against medical advice."[5] Age and enrollment are determined from the Beneficiary Summary Files, while type of discharge is reported in the Inpatient Files. To maximize sample size, we do not include the optional requirement of 12 months of continuous enrollment prior to the index stay.

In this study, our quality composite is not limited to survival without an unplanned readmission, but also incorporates whether a patient "returns to the community" rather than remaining institutionalized. Under the Improving Medicare Post-Acute Care Transformation Act of 2014, discharge to the community was adopted as an interim quality metric (Centers for Medicare and Medicaid Services 2019g). We require discharge to the community during the episode window for the last claim from an institutional setting that began during the window (Inpatient, Skilled Nursing Facility and Hospice Files).[6]

In prior studies, our composite rate of favorable outcomes specified that every outcome be favorable. Thus, a patient who died experienced an unfavorable outcome, and a patient with an unplanned readmission also experienced an unfavorable outcome, and to an equal degree. This specification, while simple, is unrealistic. There is a large body of evidence on how health relates to quality of life (for example, with limb amputation for a person with diabetes), yet we have not been able to find estimates of the "decrement" to quality of life that results from institutionalization for health reasons. To assess this impact, we build on an approach developed by Cutler and Richardson (1997).

4. The version of the readmission algorithm we use requires a 30-day gap between index stays. Because our episodes last 90 days after discharge from the index stay, we modify the SAS algorithm accordingly.

5. For its purposes, CMS excludes candidate stays in which the patient dies before discharge. We modify the SAS code so as not to exclude these episodes.

6. For examples of high-quality treatment outcomes in other contexts, see Shapiro, Shapiro, and Wilcox (2001) for cataract surgery and Berndt et al. (2002) for medical treatment of depression.

In particular, we use self-reported health outcomes to calculate a quality-adjusted life year (QALY) measure for being in an institutionalized setting. A QALY is a measure of health from 0 to 1 where 1 indicates a year of life in perfect health and 0 is death; this metric has been suggested as an approach to quality adjustment in assessments of health care productivity. To create a QALY metric for our purposes, we use the Medicare Current Beneficiary Survey (MCBS) for the years 1999–2013, which contains information on a sample of over 10,000 Medicare beneficiaries each year with information on self-reported health (i.e., excellent, very good, good, fair, and poor) and whether they reside in an institutionalized setting. We assume that individuals respond to the self-reported health question using latent information about their true health. We relate this latent health information to covariates by estimating an ordered probit of self-reported health on covariates of age, sex, and whether individuals reside in an institution. We find that being in an institution has a large negative impact on self-reported health. To obtain a QALY estimate, the cut points in the ordered probit are used to rescale the coefficient to a QALY scale, where it is assumed that the cut point for "excellent" health corresponds to a QALY of 1 and the cut point for "poor" corresponds to a QALY of 0, which is equivalent to death. Based on these estimates we find that being in an institution has a QALY measure of 0.68. That is, the quality-of-life decrement from institutionalization is 0.32.[7]

There is some uncertainty regarding this estimate as strong assumptions are made, such as relating self-reported health to the quality of life. Moreover, the MCBS survey is based on a random sample of all Medicare beneficiaries, but the movement from being at home to an institutionalized setting after the acute events that we are studying may signal a declining health trajectory. That is, the relevant comparison may not be between poor and excellent health, but rather between poor and something less than excellent health. "Very good" health would imply a QALY of 0.52 for institutionalization; that is, a larger decrement in quality of life. Merely "good" health would imply an even lower QALY value, and an even larger quality of life decrement. In view of the uncertainty, we use a quality-of-life decrement (0.66) that lies halfway between the smallest decrement just discussed (0.32 = 1.0 – QALY of 0.68 based on excellent health cut point) and the value used in our prior studies (1.0) and consider the sensitivity of our finding to these extreme alternatives.

Our framework for incorporating quality is a version of what has been called the "redefine the good" approach,[8] in contrast with the "cost of living"

7. Our baseline specification of output is therefore $\ln Y_{ht} = \ln N_{ht} + 1.4 \ln(A_{ht}\{G|A_{ht} + 0.68[1 - G|A_{ht}]\})$, in which N_{ht} is the number of episodes initiated at hospital h in year t, A_{ht} is the rate/proportion of episodes in which the patient is alive 90 days after discharge from the index stay, and $G|A_{ht}$ is the proportion of episodes with otherwise good outcomes (i.e., avoidance of an unplanned readmission *and* return to community) among those who are alive at the end of the episode window.

8. When the elasticity of quantity with respect to quality is specified to −1.4, our version places extra weight on quality, based on the evidence described above, in comparison to the

approach (Sheiner and Malinovskaya 2016). The latter was used to develop the heart attack inflation measure referenced previously (Cutler et al. 1998). These two approaches are closely related but not identical. The cost-of-living approach determines the compensating variation associated with improved outcomes from treatment. Dauda, Dunn, and Hall (2019) show that a cost-of-living index indicates greater improvement than our approach here when the value of the health improvement exceeds its incremental cost,[9] as can and sometimes does happen in health care (Cutler and McClellan 2001). While the cost-of-living approach reflects consumer welfare, Sheiner and Malinovskaya (2016) note that the rate of productivity change is the relevant metric for assessing whether providers could deliver the same number of episodes of the same quality when their reimbursement rates are reduced, as the Affordable Care Act mandates according to the rate of productivity growth outside the heath care sector. As with the BLS conceptualization of productivity (Harper et al. 2010), our focus is on producers/firms.

Turning to production inputs, the comparative returns to capital, labor, and other factors are not of interest here, and so we combine the resources used in providing care (see, e.g., Chandra and Staiger 2007; Chandra et al. 2016; Doyle 2011; Skinner and Staiger 2015), aggregating all episodes of each type at each index hospital-year. To do so, we identify claims that overlapped with each episode, including inpatient (short-term acute-care hospitals but also long-term care hospitals and inpatient rehabilitation facilities), outpatient facilities, professional (e.g., a claim submitted by a doctor for an inpatient surgery or an office visit), skilled nursing facilities (SNFs), home health, durable medical equipment, and hospice. The Carrier File of professional claims was the largest of these; in the 2014 File, the 20 percent sample included 178 million claims, with 24.6 million of these corresponding to Medicare beneficiaries experiencing a heart attack episode over 2002–2014 and 5.3 million falling within a heart attack episode window. Where a claim in any file did not fall entirely within the episode timeframe, we allocate costs based on the proportion of days with overlap.

CMS claims do not directly report costs, but instead provide a measure of resource use. For example, total charges are reported for hospital stays. To estimate costs, we use the financial reports that institutional providers participating in Medicare are required to submit to CMS (Centers for Medicare and Medicaid Services 2019d). Hospitals, for example, report not only their actual costs, but the ratio of their charges to their costs (CCRs). So,

standard version of the redefine-the-good approach. In addition, while the approach typically defines success dichotomously, we allow success to be polychotomous according to the quality of life associated with distinct patient outcomes (see above).

9. That is, consider improved health outcomes stemming from an increase in multifactor productivity. Then the absolute value of the magnitude of the price decrease under the cost-of-living approach exceeds the magnitude of the productivity increase under the condition noted by Dauda, Dunn, and Hall (2019).

a hospital's cost for a claim is measured by linking reported charges on the claim to the hospital's reported CCR based on Medicare provider number and then multiplying the former by the latter, as is commonly done in the literature (Cutler and Huckman 2003). SNF cost reports include revenue-to-cost ratios, and so we multiply these ratios by claim-reported revenues to measure the cost of the claim.[10]

CCRs are sometimes unavailable, and our primary analysis excludes episodes for which any CCR is missing. As table 11.1 shows, this criterion excludes about 15 percent of heart attack episodes. In a sensitivity analysis, we also include episodes with one or more institutional claims that could not be matched to cost data, and whose payments for claims with missing cost data as a share of total payments for the episode type were less than or equal to the median for the episode type.[11] We then inflate total measured costs of these episodes, according payments for claims with missing costs as a share of total payments for all episodes of the same type that initiated within the same calendar year.

Professional claims report Relative Value Units (RVUs), a measure of the resources required to provide a particular service (Medicare Payment and Advisory Committee 2018). The reimbursement received by a professional is equal to the number of RVUs multiplied by a dollar-denominated "conversion factor" (CF) specified annually in CMS's Medicare Physician Fee Schedule Final Rule, adjusted for geographic differences in the cost of care (Medicare Payment and Advisory Committee 2018). One objective in setting the CF is to ensure that professional providers offer accessible care to beneficiaries, yet federal policy makers have intervened in the CF-setting process to postpone reductions in professional payments mandated by statute for the purpose of controlling cost growth (Guterman 2014). We assume that the CF in 2002 equated aggregate professional revenues with aggregate costs in that year, before the interventions began. We do not include prescription drug costs due to data limitations during the first five years of our analytic period (Medicare Part D was introduced in 2006).

We wish to measure the real cost of treating episodes. As an input into its reimbursement policy making, CMS constructs and reports "market basket indices" and the Medicare Economic Index (MEI). The Inpatient Hospital market basket index, for example, measures changes in the cost of providing inpatient hospital care. We use this index and those for other institutional settings to deflate nominal costs into real 2014 dollars. The MEI is used for professional payment, and measures inflation in the cost of providing professional services, less an adjustment for productivity growth in the economy at large (2012 Medicare Economic Index Technical Advisory Panel 2012).

10. Charges are not in general equal to payments in health care—due, for example, to contractual discounts off list price for commercial insurers as well as administrative pricing for Medicare and other public payers (Reinhardt 2006).

11. We include payments from all sources.

We inflation-adjust professional costs by reversing the productivity adjustments to the MEI; durable medical equipment costs are similarly deflated.

Turning to patient severity ($\boldsymbol{S}_{ht}$), a key measure comes from the Agency for Healthcare Research and Quality's Inpatient Quality Indicators (IQIs) (Agency for Healthcare Research and Quality 2019). The IQIs were developed for the purpose of assessing the quality of care across hospitals and over time using standard administrative data (specifically, patient discharge records, which typically lack post-discharge outcomes, including mortality). The IQIs include inpatient mortality for a variety of conditions, including the six episode types for which CMS reports mortality. In order to reliably assess mortality performance, teams of clinical experts developed risk adjustment models that can be applied to individual hospitalizations (including patients who actually died during their stays). For each episode type, we use the average predicted likelihood of survival through the end of hospitalization, derived from these models, averaged across all episodes (including patients who died during stays) initiated at an index hospital in a year. Table 11.1 reports that predicted survival was not available for some episodes that are consistent with the CMS readmission algorithm. For heart attack, the IQI excludes cases whose status as the first or subsequent heart attack was not coded, while the readmission algorithm does not. For the six episode types with IQI risk models, we limit our analytic sample to episodes with predicted inpatient mortality for the sake of clinical specificity. Details of the IQI inclusion/exclusion criteria for heart attack episodes are shown in table 11A.1.

An important element of these risk models is the All Patients Refined Diagnosis Related Group (APR-DRG)—in particular, its risk of mortality scale. While the inputs into the APR-DRGs are known (e.g., diagnosis and procedure codes), a limitation of our approach is that the logic of the APR-DRG "grouper" methodology is proprietary to 3M, and so is not transparent to end users. There is a limited-license version released by AHRQ for the purpose of implementing the IQIs. We apply version 6.0 of the IQIs, the last refinement developed for use with ICD-9 coding (CMS transitioned to ICD-10 beginning in fiscal year 2015). Details on the AMI risk model are shown in table 11A.2.

In addition, for all episode types (including the two for which IQI risk models were not available), we exploit diagnostic information in our data by measuring the proportion of episodes with different numbers of Charlson-Deyo comorbidities (such as dementia) recorded in the index inpatient record. These comorbidities have been demonstrated to usefully predict death within 12 months (Charlson et al. 1987; Quan et al. 2005). For heart attack episodes, we also characterize the type based on the location within the heart, using the fourth digit of the ICD-9 code (Romley, Goldman, and Sood 2015). The type of heart attack relates to prognosis; for example, survival is relatively favorable for a "non-STEMI" heart-attack (ICD-9 of 410.7x for subendocardial infarction), at least in the near term (Cantor et al. 2005; Cox et al. 2006). The maximum number of diagnoses recorded on inpatient claims increased from 10 to 25 in 2010, so we limit ourselves to the first 10.

In addition, we use the proportion of patients who were female and of various races, as reported in the Beneficiary Summary Files. These files also report the zip code in which each beneficiary resides, which we link to zip code–level data from the 2000 Census on a variety of community sociodemographic characteristics used as proxies for patient severity in prior literature (Fisher et al. 2003a; Fisher et al. 2003b; Romley, Goldman, and Sood 2015; Romley, Jena, and Goldman 2011); examples include the poverty rate and the proportion of elderly residents with self-care limitations. As table 11.1 shows, about 1,900 of 463,800 episodes initiated at hospitals for whom *none* of the patient zip codes matched to the Census data; all other episodes could be matched. Finally, we use the proportion of discharges in each quarter, as there may be seasonality in severity and fourth-quarter discharges had to be excluded in 2014 (due to incomplete follow up).

Turning to other elements of hospital production, we account for medical education. This activity may complement AMI care or draw resources from it, and it is possible that patients with particular episodes became more (or less) likely to be treated at an academic hospital over time. We address this possibility using indicator variables for intervals of the number of medical residents per bed specified in prior literature (Volpp et al. 2007); these data are available from the Impact Files released annually by CMS in support of its inpatient prospective payment system (Centers for Medicare and Medicaid Services 2019b). Small and largely rural hospitals are not paid under this system, and so episodes initiated at these hospitals are excluded from the analytic sample (see table 11.1).

Our regressions clustered standard errors at the level of the index hospital. Because of our logarithmic specification, hospital-years with a zero rate for a favorable health outcome are excluded from the analysis; table 11.1 shows that 2.7 percent of AMI episodes treated at 8.0 percent of hospitals are excluded on this basis. For representativeness, our regressions weighted hospital-year observations by their number of episodes. In further sensitivity analysis, we include fixed effects for the hospitals at which episodes were initiated. This specification aims to deal with the possibility that unmeasured heterogeneity between providers (including MFP differences) was systematically related to patient severity or teaching status, leading to bias in our estimates of the trajectory of MFP over time.

Finally, in order to develop some insight into aggregate productivity growth in the delivery of acute episodes of care, we create a composite that combines all episode types. To do so, we weight the annualized growth rate for each episode type by the episode's share of total cost in various base years.

11.3 Findings

Before reviewing our regression results, we first describe the episodes studied, with a focus on AMI—that is, heart attack. Table 11.2 reports sample statistics for the heart attack analysis. Across 28,635 index hospital-years, the average date of the initial admission is mid-2007. The average cost per episode is $37,200 in 2014 dollars. Of elderly Medicare beneficiaries admitted to a hospital with a heart attack, 79.4 percent survived at least 90 days beyond the initial discharge. The AHRQ AMI IQI predicts that 92.2 percent would have survived beyond the initial hospital stay (though not necessarily 90 days beyond discharge). Among 90-day survivors, 85.1 percent avoided an unplanned readmission within 30 days of initial discharge. Among survivors without a readmission, 81.6 percent were discharged home from their final institutional encounter.

In terms of severity, roughly two thirds of episodes involved a non-STEMI heart attack. All episodes involved at least one Charlson-Deyo comorbidity, as a heart attack is such a comorbidity. More than 7 in 10 episodes involved additional comorbidities. The average age of beneficiaries was 78.8 years, slightly less than half were female, and almost 9 in 10 were white. Median household incomes in beneficiaries' zip codes averaged $42,600 in the 2000 Census. In terms of index hospital characteristics, slightly more than 4 in 10 episodes took place at facilities with no medical residents, while about 3 in 20 took place at a major teaching hospital (> 0.25 residents per bed).

A simple albeit limited measure of productivity is the cost of a heart attack episode, irrespective of patient severity or outcomes (Ashby, Guterman, and Greene 2000). Figure 11.1 shows this measure over 2002–2014. The cost of an episode was $34,500 in 2002, measured in 2014 dollars. The cost was reasonably flat thereafter but did increase to $35,700 by 2014. The top panel of figure 11.2 shows that average cost increased for every episode type except LEJR. Hip fracture increased the most in absolute terms ($5,100), while GI bleed increased the most in relative terms (20.0 percent).

In 2014, the total cost of all of these episodes was $38.3 billion, measured in 2014 dollars.[12] Focusing on the three episode types from our prior study (heart attack, heart failure, and pneumonia), the total cost was $16.9 billion in 2014. Limiting ourselves to the cost of the initial hospital stays (as in the prior study), the total for these three episode types was $7.8 billion. For heart attack alone, the total cost of initial hospital stays in 2014 was $2.8 billion.

12. Total costs in our analytic sample were multiplied by a factor of five, because we had access to a 20 percent sample of beneficiaries. In 2014, incomplete follow up (due to lack of 2015 data) required that episodes be initiated before October. Accordingly, we inflated 2014 costs by the ratio of the number of January–December episodes to the number of January–September episodes over 2002–2013. Finally, we eliminated duplicates in cases that corresponded to multiple episode types (for example, some patients with hip fracture underwent LEJR).

Table 11.2 Sample statistics for AMI episodes

Variable	Mean (SE)
Episodes, *n*	402,778
Hospitals, *n*	3,560
Hospital-years, *n*	28,635
Year of admission	2007.3 (3.7)
Cost per episode (000s of 2014 dollars)	\$37.2 (\$14.1)
Survival of episode	79.4% (12.6%)
No unplanned readmissions (30 day) among survivors	85.1% (12.0%)
Discharge home among survivors without readmissions	81.6% (15.9%)
AHRQ predicted inpatient survival	92.2% (3.8%)
Location of heart attack: Anterolateral (410.0x)	2.1% (3.7%)
Location of heart attack: Other anterior wall (410.1x)	8.1% (7.6%)
Location of heart attack: Inferolateral wall (410.2x)	1.7% (3.4%)
Location of heart attack: Inferoposterior wall (410.3x)	1.2% (2.7%)
Location of heart attack: Other inferior wall (410.4x)	9.9% (8.2%)
Location of heart attack: Other lateral wall (410.5x)	1.2% (2.8%)
Location of heart attack: True posterior wall (410.6x)	0.3% (1.5%)
Location of heart attack: Sub-endocardial (410.7x)	68.3% (16.8%)
Location of heart attack: Other specified sites (410.8x)	1.4% (4.6%)
Location of heart attack: Unspecified site (410.9x)	5.9% (9.5%)
No Charlson-Deyo comorbidity	0.0% (0.0%)
1 Charlson-Deyo comorbidity	27.7% (13.1%)
2 Charlson-Deyo comorbidities	32.3% (12.7%)
3 Charlson-Deyo comorbidities	21.0% (11.5%)
4 Charlson-Deyo comorbidities	11.2% (9.3%)
5+ Charlson-Deyo comorbidities	7.8% (8.5%)
Age	78.8 (3.1)

(*continued*)

Table 11.2 (cont.)

Variable	Mean (SE)
Female	49.0% (14.6%)
White	88.0% (15.6%)
African American	7.7% (12.8%)
Hispanic	1.8% (5.9%)
Other race	2.5% (6.9%)
Patient zip code characteristics	
Median household income ($000)	$42.6 ($10.1)
Social Security income ($000)	$11.3 ($0.9)
Poor	12.0% (4.9%)
Employed	94.3% (2.0%)
Less than high school education	20.0% (6.7%)
Urban	70.3% (21.9%)
Hispanic	8.7% (12.3%)
Single	41.7% (4.6%)
Elderly in an institution	5.5% (2.4%)
Noninstitutionalized elderly with physical disability	29.3% (4.7%)
Mental disability	11.0% (2.9%)
Sensory disability among elderly	14.6% (2.6%)
Self-care disability	9.7% (2.6%)
Difficulty going-outside-the-home disability	20.5% (3.6%)
Index hospital characteristics	
No residents	43.2% (49.5%)
Residents per bed > 0 and ≤ 0.25	41.2% (49.2%)
Residents per bed > 0.25 and ≤ 0.6	10.7% (30.9%)
Residents per bed > 0.6	5.0% (21.7%)

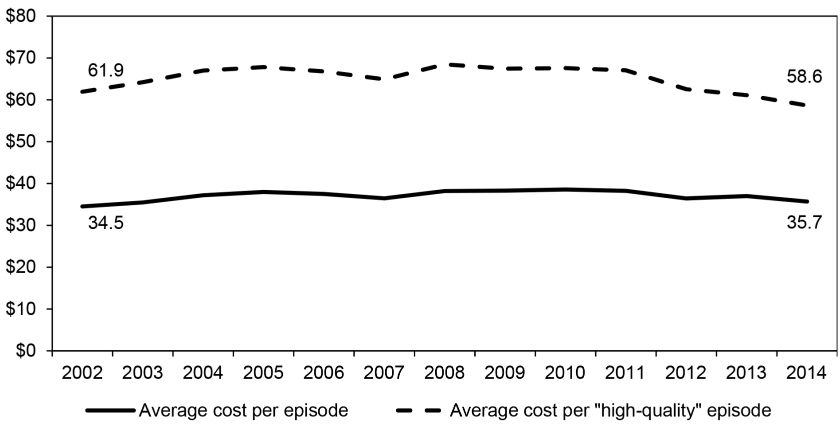


Fig. 11.1 Cost of heart-attack episodes (000s of 2014 dollars)

Notes: In this figure, a "high-quality" episode means that the patient survived through the end of the episode, avoided an unplanned readmission within 30 days of the initial discharge, and was discharged home from the last facility claim. This definition corresponds to a quality of life decrement for institutionalization of –1.0. Regression analyses considered alternative decrements, with the intermediate value of –0.66 as the baseline. Under this baseline, an episode in which the patient survived but was institutionalized is counted as 34% of an episode with survival without institutionalization.

The simple measures shown in the top panel of figure 11.2 ignore the quality of the health outcomes delivered to patients. Figure 11.3 shows that survival improved for heart attack patients, rising from a rate of 77.8 percent in 2002 to a rate of 82.8 percent in 2014. Among survivors, the rate of avoidance of unplanned readmission within 30 days of initial discharge improved from 83.5 percent to 86.8 percent. The rate of discharge to home from the last facility claim declined somewhat, from 84.4 percent in 2002 to 83.4 percent in 2014.

Defining a high-quality episode as survival without institutionalization (whether an unplanned readmission or a discharge to another facility), figure 11.3 shows that the rate of high-quality episodes increased from 55.7 percent in 2002 to 60.8 percent in 2014 for heart attack patients. The middle panel of figure 11.2 shows the rate of high-quality episodes for all episode types. This rate improved for six of the eight episode types; the increase was greatest in absolute terms for hip fracture (5.8 percentage points) and in relative terms for LEJR (18.7 percent). The rate of high-quality stays declined by 3.6 percentage points for heart failure episodes. Among these patients, avoidance of readmission improved, but survival and home discharge rates worsened.

Figure 11.1 shows that the improvement in patient outcomes dominated the modest rise in costs for heart attack patients. The cost of a high-quality heart attack episode decreased from $61,900 in 2002 to $58,600 in 2014.

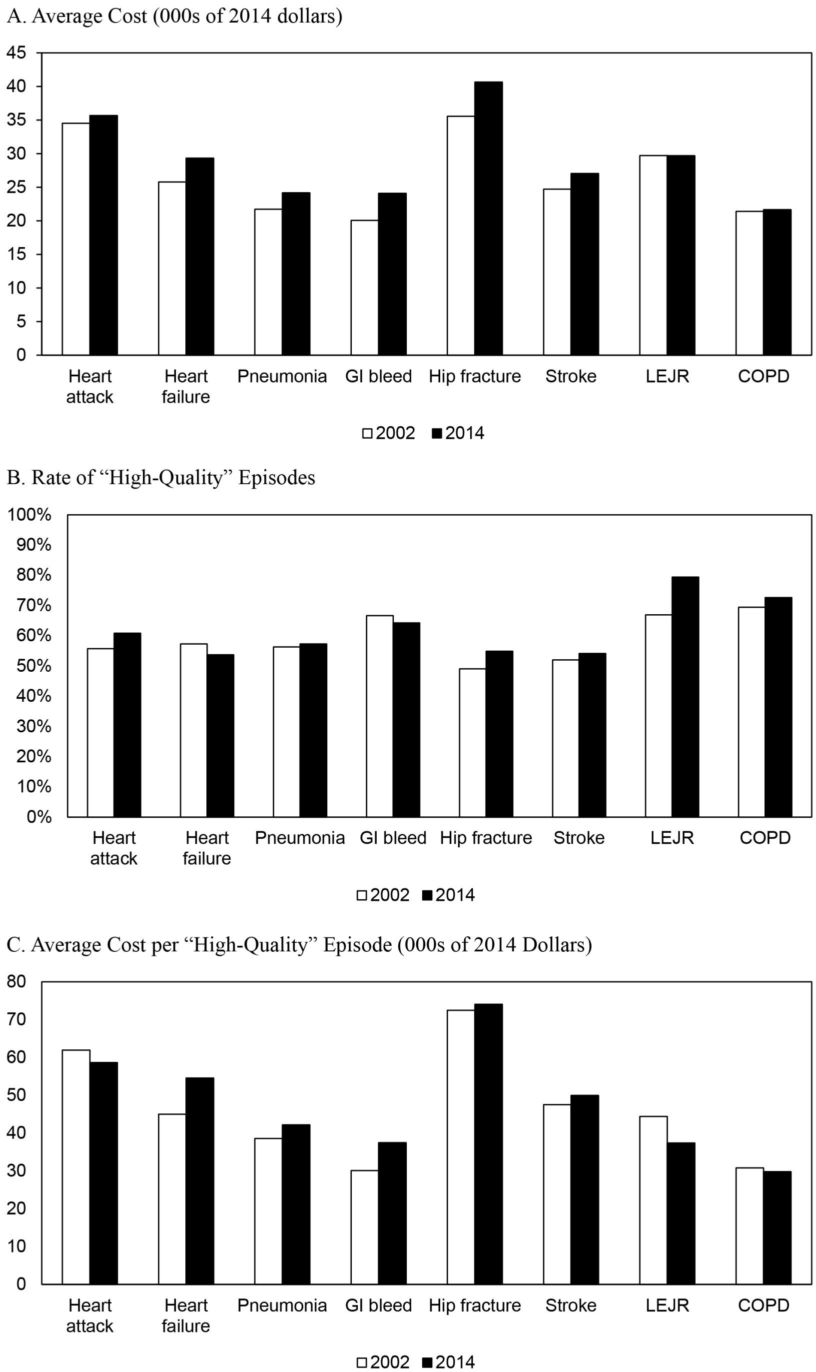


Fig. 11.2 Episode cost and quality

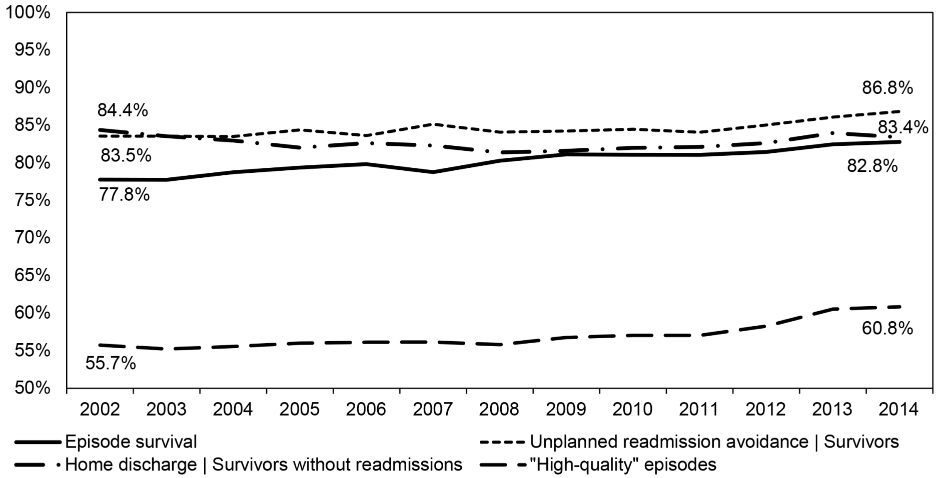


Fig. 11.3 Rates of favorable patient outcomes among heart-attack episodes

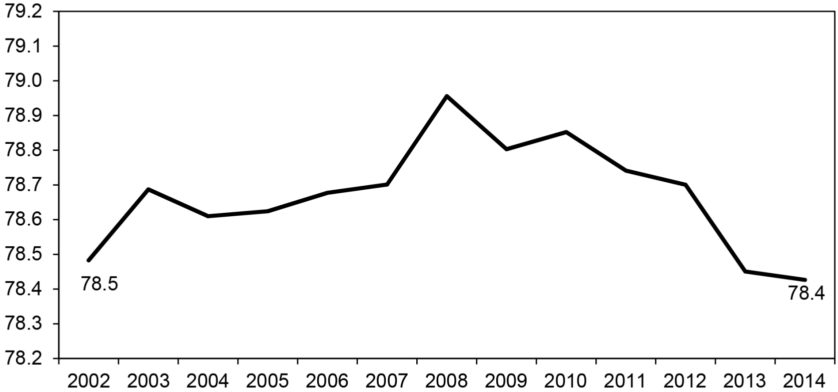
Notes: In this figure, a "high-quality" episode means that the patient survived through the end of the episode, avoided an unplanned readmission within 30 days of the initial discharge, and was discharged home from the last facility claim. This definition corresponds to a quality of life decrement for institutionalization of –1.0. Regression analyses considered alternative decrements, with the intermediate value of –0.66 as the baseline. Under this baseline, an episode in which the patient survived but was institutionalized is counted as 34% of an episode with survival without institutionalization.

Figure 11.2 shows the cost of high-quality episodes for all episode types. This cost increased for five episodes—namely, heart failure, pneumonia, GI bleed, hip fracture, and stroke. For heart failure, costs increased as quality decreased, and this episode type experienced the largest absolute increase in the cost of a high-quality episode ($9,600). GI bleed had the largest relative increase (24.6 percent). The higher costs for pneumonia, hip fracture, and stroke outweighed their quality improvements. The cost of a high-quality episode decreased for LEJR and COPD in addition to heart attack. This decrease was largest in both absolute and relative terms for LEJR (–$7,000 and –15.8 percent, respectively).

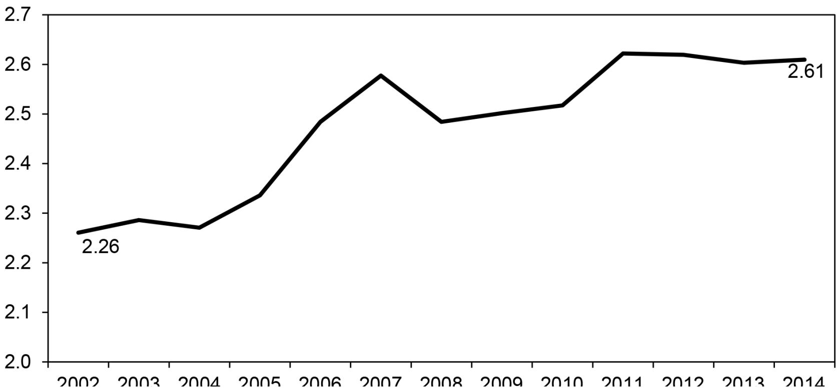
These changes in the cost of a high-quality episode may have reflected trends in the severity of patients treated. Figure 11.4 shows that the age of a heart attack patient at index admission was 78.6 years in 2002, and then rose steadily to a maximum of 79.0 years in 2008, before declining to its starting value of 78.6 years in 2014. The number of Charlson-Deyo comorbidities recorded on the index inpatient record of a heart attack patient increased substantially over time, from 2.27 in 2002 to 2.61 in 2014. The predicted likelihood of inpatient survival from the AHRQ IQI risk model decreased from 93.3 percent to 92.8 percent over the period.

Using all our patient severity measure and the results of our primary

A. Average Age at Admission



B. Number of Charlson-Deyo Comorbidities on Index Inpatient Record



C. Predicted Inpatient Survival from AHRQ Inpatient Quality Indicator Risk Model

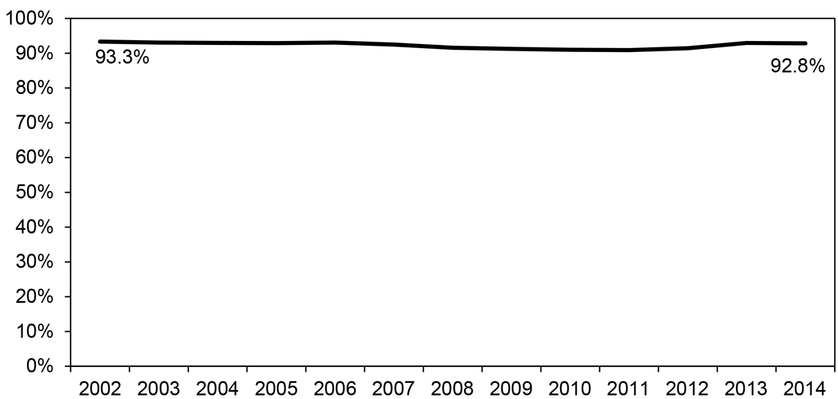


Fig. 11.4 Select patient severity measures for heart-attack episodes

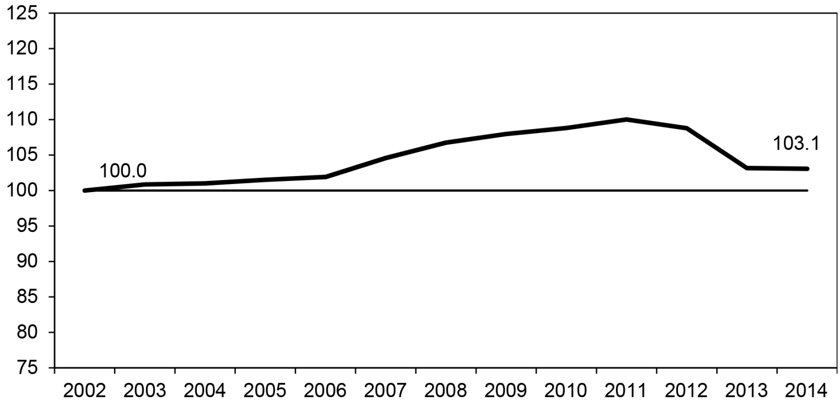


Fig. 11.5 Patient severity index among heart-attack episodes

Note: We construct the patient severity index by exponentiating $-\bar{S}_{ht}\hat{\beta}_S$, obtaining $\hat{\beta}_S$ from the regression results corresponding to Figures 16 and 17 and normalizing the index to a value of 100 in 2002.

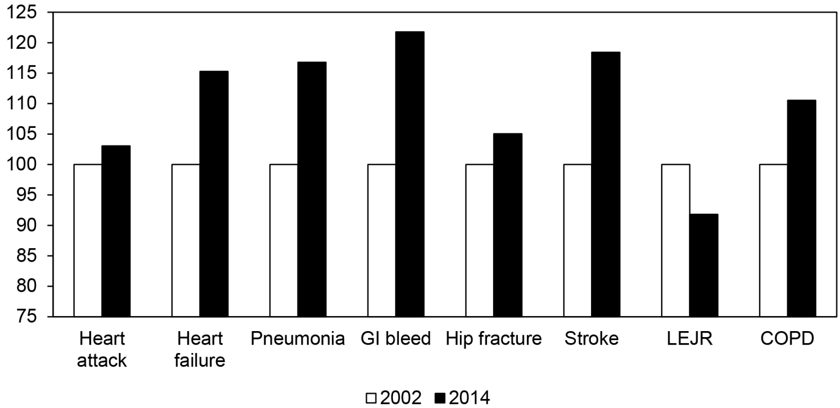


Fig. 11.6 Patient severity index among all episodes

Note: We construct the patient severity index by exponentiating $-\bar{S}_{ht}\hat{\beta}_S$, obtaining $\hat{\beta}_S$ from the regression results corresponding to Figures 16 and 17 and normalizing the index to a value of 100 in 2002.

regressions, we can construct a patient severity index.[13] For heart attack episodes, figure 11.5 shows that severity increased from its baseline value of 100 in 2002, started to rise more rapidly in 2007 and reached a peak of 110.0 in 2010, then settled at 103.1 in 2014. This pattern means that the heart attack patients treated in 2014 would have required 3.1 percent higher costs to enjoy the same outcomes as patients in 2002. Figure 11.6 shows the

13. The construction of the index is described in the note to figure 11.5.

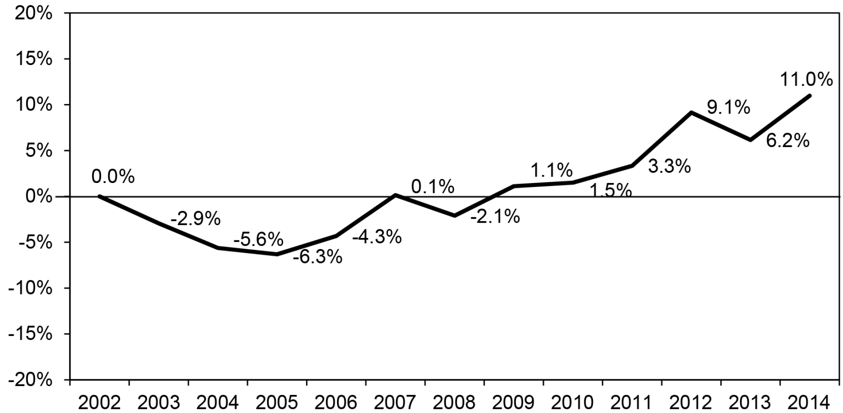


Fig. 11.7 Cumulative change in productivity since 2002 in treating heart-attack episodes

patient severity index for all episode types. LEJR experienced a decline in severity even as its cost of a high-quality episode decreased. Severity rose for all other episode types. GI bleed saw the largest increase, with an index value of 121.8 in 2014.

In addition to the severity index, we can construct an index for other hospital production—specifically, the effect (whether positive or negative) of medical education on the delivery of our acute episodes. As appendix figure 11A.2 shows for heart attack episodes, teaching status played little role in changes in productivity in treating these episodes.

Focusing on our regression analyses, the trajectory of estimated productivity for heart attack episodes appears in figure 11.7. Productivity declined at first, reaching a trough of –6.3 percent cumulative growth since 2002, before beginning to improve fairly consistently, reaching a maximum of 11.0 percent improvement (over 2002) by 2014. A similar pattern was observed in our prior studies of hospital and nursing home stays (Romley, Goldman, and Sood 2015; Gu et al. 2019). The productivity trajectories for all episode types are shown in appendix figure 11A.3; complete regression results are reported in appendix table 11A.3.[14]

14. In general, the regression coefficients have the expected signs. For the six episode types for which IQI risk models are available, a higher predicted probability of surviving beyond the initial hospital stay is associated with better outcomes or lower costs. For example, a 1 percent increase (relative, not absolute) in the average survival probability of stroke patients is associated with 4.1 percent more stays or better outcomes (given costs), or 4.1 percent lower costs (given the number of episodes and their quality). Likewise, having fewer Charlson-Deyo comorbidities recorded on the initial hospital record is associated with greater output or lower costs. For LEJR, for example, if all patients had only one comorbidity, output would be roughly 12 percent greater, or costs 12 percent lower. Finally, for all episode types except heart attack,

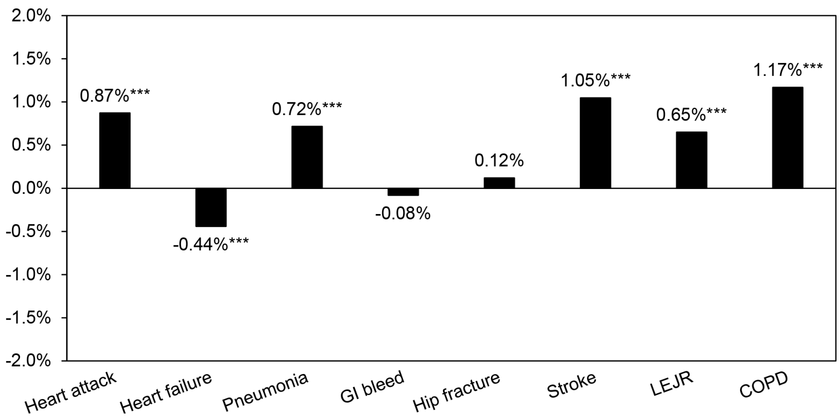


Fig. 11.8 Annualized rate of productivity growth, 2002–2014

Notes: Rates calculated according to the formula $\exp(\hat{b}_{2014} / 12) - 1$, in which $\hat{b}_{2014}$ is the regression coefficient corresponding to episodes starting in 2014, relative to 2002. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

On an annualized basis, productivity for heart attack episodes grew by 0.87 percent on average between 2002 and 2014. Figure 11.8 shows somewhat slower growth for pneumonia and LEJR, but even greater improvement (in excess of 1.0 percent per year) for stroke and COPD. Productivity change for GI bleed and hip fracture was indistinguishable from zero. For heart failure episodes, productivity is estimated to have decreased by 0.44 percent per year on average.

Figure 11.9 shows the impact of adjustments for patient severity and outcome quality on the estimates just reported. As noted previously, severity increased for all episode types except LEJR. Consequently, estimated productivity growth is lower when we adjust for patient severity than when we do not (0.65 percent versus 1.37 percent per year). Among the episode types experiencing greater severity, the sign of estimated productivity growth changes from positive to negative for pneumonia and stroke when we ignore severity. Severity adjustment plays a relatively limited role for heart attack (+0.87 percent with versus +0.62 percent without).

Ignoring quality, the point estimates for annual productivity growth are negative for every episode type except COPD. Even in the latter case, estimated productivity improvement is 0.51 percent per year when quality is ignored, versus 1.17 percent per year otherwise. For heart failure, quality

a younger patient population is associated with more output or lower costs. For pneumonia, for example, a 1 percent decrease in average age is associated with 2.1 percent more output or lower costs.

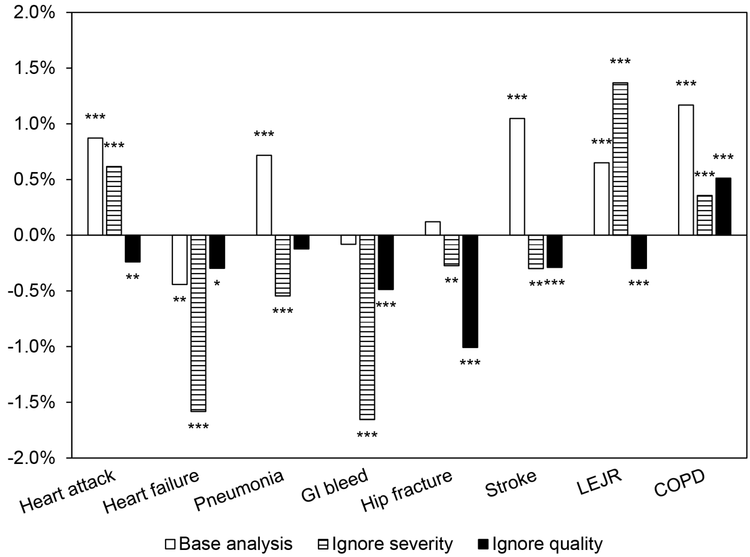


Fig. 11.9 Impacts of adjustment for outcome quality and patient severity on annualized productivity growth estimates

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

adjustment results in somewhat more negative growth (−0.44 percent per year versus –0.30 percent per year), because quality declined in the aggregate.

The results thus far assume that institutionalization (whether unplanned readmission or discharge to another facility) causes a decrease in quality of life of −0.66. That is, survival with institutionalization is 34 percent as good as survival without institutionalization. As noted previously, there is substantial uncertainty about the impact of institutionalization on quality of life. Figure 11.10 considers two alternatives spanning our baseline value; namely, −0.32 and −1.0. Where trends in institutionalization rates are favorable, a smaller (in absolute magnitude) decrement implies that measured productivity growth will be slower. For example, with a decrement of 0.32, productivity growth for heart attack episodes is 0.72 percent per year, instead of 0.87 percent with the baseline intermediate value. With a decrement of 1.0, growth is higher; namely, 1.06 percent per year. For hip fracture, the baseline estimate is an insignificant +0.12 percent per year, but significant at +0.78 percent and –0.23 percent per year with decrements of 1.0 and 0.32, respectively. Productivity growth for LEJR episodes is also sensitive in magnitude (if not the positive direction) to the decrement value.

For the elasticity of quantity with respect to quality, our baseline value is

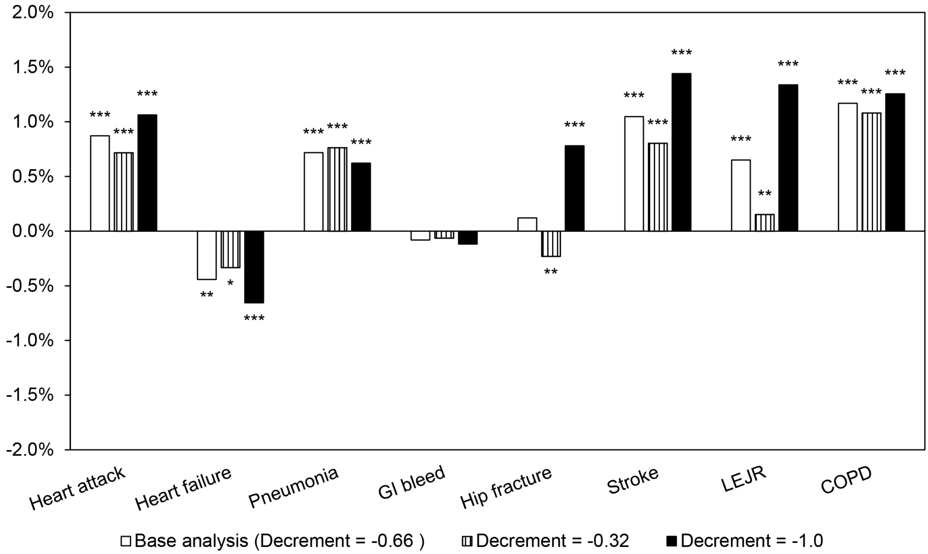


Fig. 11.10 Sensitivity of annualized productivity growth estimates to quality of life decrement for institutionalization

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

−1.4, based on our view of the best evidence (discussed previously). We also consider a value of −1.0, consistent with prior studies (Romley, Goldman, and Sood 2015; Gu et al. 2019; Romley et al. 2019). With this alternative value, a 10 percent improvement in quality requires a 10 percent decrease in the number of episodes, instead of 14 percent according to the baseline value. Consequently, measured productivity growth, given a favorable quality trend, is slower under this alternative value. Figure 11.11 is consistent with this observation, but further shows that estimated growth is not particularly sensitive to this alternative value for the elasticity. For hip fracture, insignificant growth of +0.12 percent per year becomes a marginally significant decline of 0.20 percent per year.

As noted previously, cost data are unavailable for some facility claims (15 percent of heart attack episodes had at least one such claim). We assess the sensitivity of estimated productivity growth rates to the inclusion of episodes with some (but relatively limited) missingness, with their measured total costs inflated according to payments on claims with missing costs in comparison to total payments for such episodes in each year. Figure 11.12 shows that the changes to our estimates are negligible.

Finally, we assess the sensitivity of our estimates to the inclusion of fixed effects for hospitals. As figure 11.13 shows, measured productivity growth

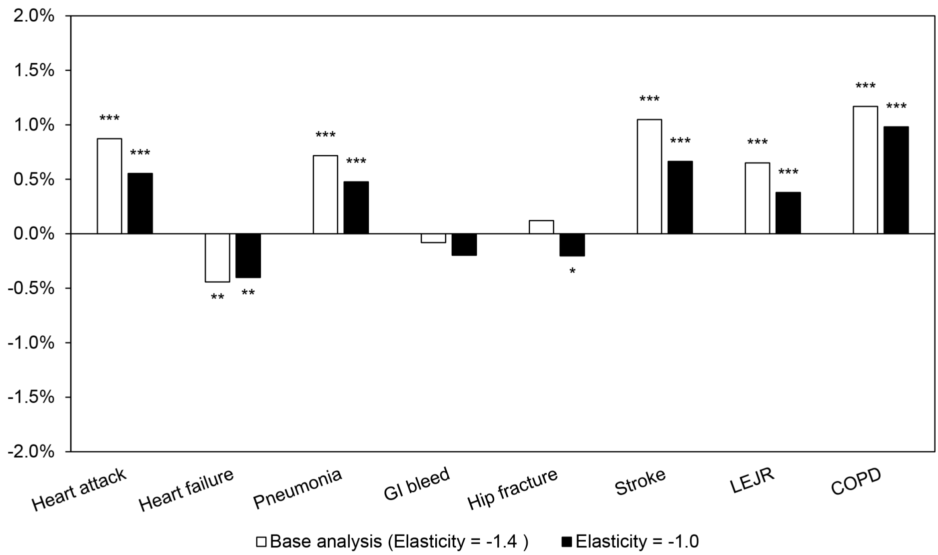


Fig. 11.11 Sensitivity of annualized productivity growth estimates to elasticity of episode quality with respect to quantity

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

becomes faster for every episode type. Indeed, growth for heart failure is no longer significantly negative, and the rate for hip fracture is now significantly positive, at +0.40 percent per year.

Based on our baseline results, composite productivity growth, aggregated across all episode types, is shown in figure 11.14. The growth rate is +0.44 percent per year on average over 2002–2014 when productivity is aggregated based on cost shares using 2002 shares as the base, and +0.45 percent and +0.44 percent when using cost shares from 2008 and 2014, respectively.

11.4 Conclusion

There is widespread concern about poor coordination in US health care. Even if hospitals or doctors improve their productivity over time, information and incentive problems across providers could result in stagnant performance with respect to episodes of care. Policy makers and health practitioners are increasingly scrutinizing the performance of the health care system in delivering episodes of care.

To our knowledge this is the first study that assesses productivity growth—from the producer perspective, consistent with the focus of BLS—in the provision of acute episodes of care. We consider eight types of episodes delivered to Medicare fee-for-service beneficiaries over 2002–2014. Drawing

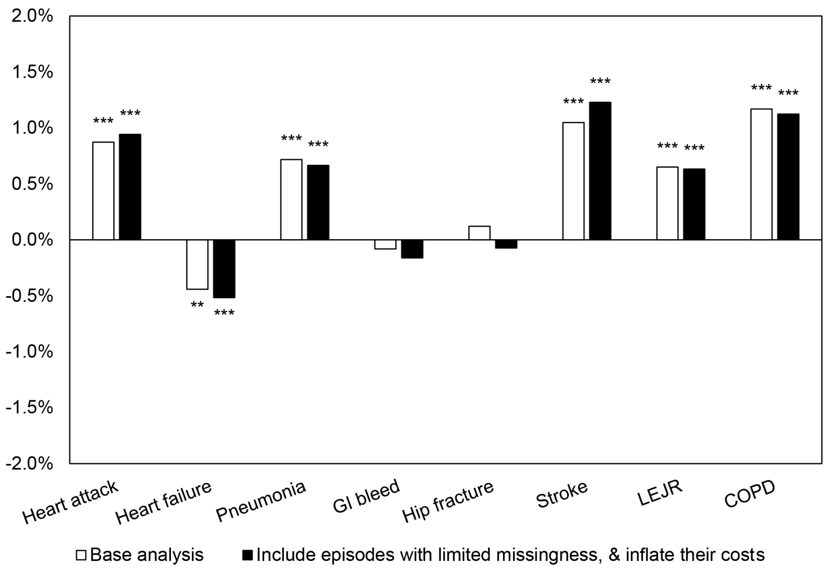


Fig. 11.12 Sensitivity of annualized productivity growth estimates to treatment of missing episode costs

Notes: "Limited" missingness refers to episodes with (a) one or more institutional claims that could not be matched to cost data, and (b) whose payments for claims with missing cost data as a share of total payments for the episode was at or below the median for the episode type. Total measured costs for these episodes were inflated according to payments for claims with missing costs as a share of total payments for all episodes of the same type that initiated in the same calendar year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

on insurance claims and administrative data, we find positive multifactor productivity growth for a majority of the episode types. For stroke and chronic obstructive pulmonary disease, our baseline estimates of the rate of productivity growth over this period exceed 1 percent per year. There is, however, some evidence of negative productivity growth for heart failure. Our findings for the various episode types are fairly robust to alternative assumptions.

To develop some insight into aggregate productivity growth for these episodes, we constructed a composite measure, and found an annual growth rate of roughly 0.45 percent. The cost of care provided under Medicare Parts A and B for these episodes totaled $38 billion in 2014, measured in 2014 dollars, compared to overall program spending of $367 billion (Cubanski, Neuman, and Freed 2019). While this total is substantial, there is clearly an opportunity to address productivity in health care delivery more broadly. One potentially worthwhile direction would be to assess multifactor productivity in the treatment of various chronic conditions. Berndt et al. (2002) have already considered depression, while Eggleston et al. (2011) have addressed

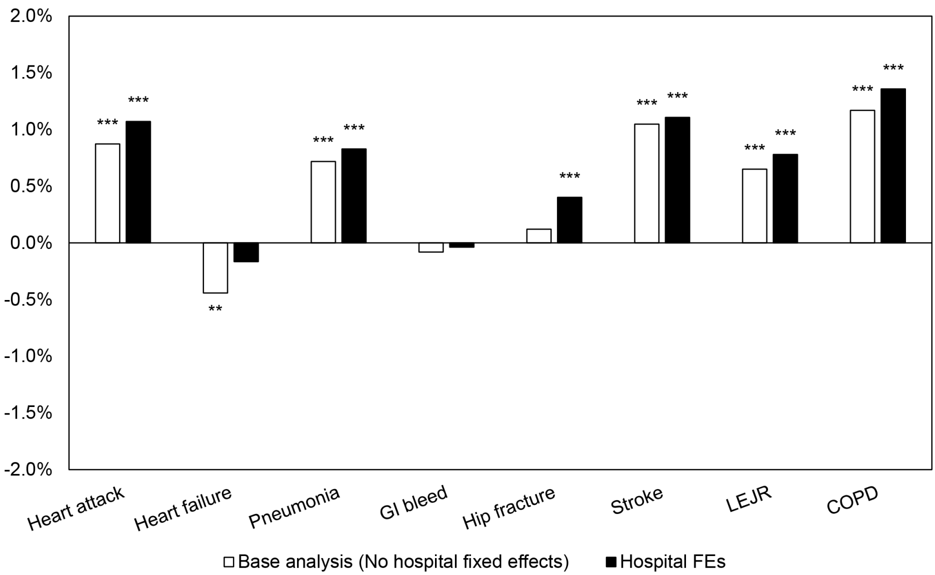


Fig. 11.13 Sensitivity of annualized productivity growth estimates to inclusion of hospital fixed effects

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

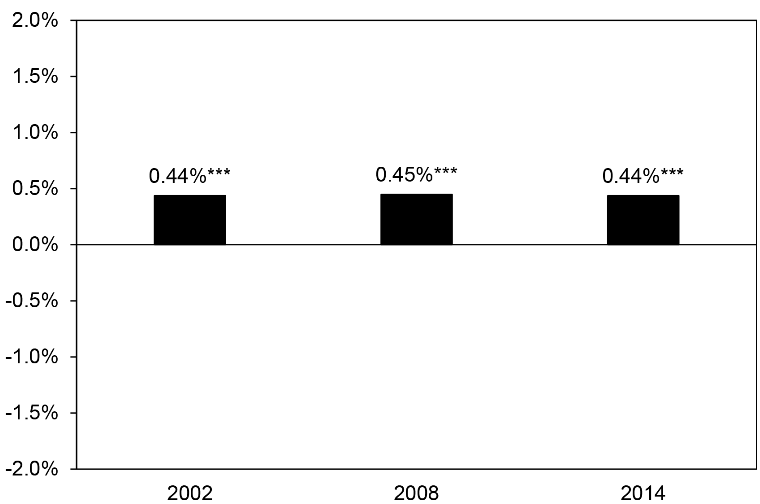


Fig. 11.14 Annualized growth of composite (all-episode-type) productivity according to base year

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

productivity in diabetes, but from the consumer welfare perspective. In our view, and with these studies as motivating examples, such analyses will be most credible when well informed by clinical science, as well as economic practice.

For the episodes studied here, the reasonably favorable picture that emerges stems in substantial part from our efforts to account for the quality of the health outcomes experienced by patients. We measure quality based on patient survival, avoidance of unplanned readmission, and discharge to the community. The latter is of relevance to recent federal policy concerning post-acute care, and we found in auxiliary analysis that continued institutionalization rather than community discharge entails a substantial decrement to a patient's quality of life. For most episode types, these outcomes improved over time, substantially impacting measured productivity growth. For example, productivity growth for stroke is estimated to be +1.05 percent per year when we account for quality of care, but −0.29 percent per year if we ignore it. The importance of quality adjustment has long been recognized in the measurement of health care price indices that focus on consumer welfare (Cutler et al. 1998).

There is general agreement among experts that the output of the health care sector should be measured based on the treatments of the conditions, rather than the individual services (e.g., physician visit), which are inputs to those treatments (National Research Council 2010; World Health Organization 2011; Moulton 2018). To improve national economic measurement of the health care sector, the Bureau of Economic Analysis has recently developed a Health Care Satellite Account that tracks spending for 261 conditions (Dunn, Rittmueller, and Whitmire 2016; Dunn et al. 2018). However, this new account does not address quality of care at present. Our study strongly suggests that quality is a critical element for properly measuring output of the health care sector and our approach may point in a useful and practical direction. In addition, improved measurement of multifactor productivity in the health care system should contribute to a better understanding of the drivers, in terms of economics and policy, of system performance.

Appendix

Table 11A.1 AHRQ inpatient quality indicator for AMI

AHRQ Quality Indicators™ (AHRQ QI™) ICD-9-CM Specification Version 6.0 Inpatient Quality Indicator 15 (IQI 15) Acute Myocardial Infarction Mortality Rate March 2017

Provider-Level Indicator Type of Score: Rate

Prepared by:

Agency for Healthcare Research and Quality

U.S. Department of Health and Human Services www.qualityindicators.ahrq.gov

Description

In-hospital deaths per 1,000 hospital discharges with acute myocardial infarction (AMI) as a principal diagnosis for patients ages 18 years and older. Excludes obstetric discharges and transfers to another hospital.

[NOTE: The software provides the rate per hospital discharge. However, common practice reports the measure as per 1,000 discharges. The user must multiply the rate obtained from the software by 1,000 to report in-hospital deaths per 1,000 hospital discharges.]

Numerator

Number of deaths (DISP=20) among cases meeting the inclusion and exclusion rules for the denominator.

Denominator

Discharges, for patients ages 18 years and older, with a principal ICD-9-CM diagnosis code for AMI.

AMI diagnosis codes: (MRTAMID)

41000	AMI ANTEROLATERAL, UNSPEC	41050	AMI LATERAL NEC, UNSPEC
41001	AMI ANTEROLATERAL, INIT	41051	AMI LATERAL NEC, INITIAL
41010	AMI ANTERIOR WALL, UNSPEC	41060	TRUE POST INFARCT, UNSPEC
41011	AMI ANTERIOR WALL, INIT	41061	TRUE POST INFARCT, INIT
41020	AMI INFEROLATERAL, UNSPEC	41070	SUBENDO INFARCT, UNSPEC
41021	AMI INFEROLATERAL, INIT	41071	SUBENDO INFARCT, INITIAL
41030	AMI INFEROPOST, UNSPEC	41080	AMI NEC, UNSPECIFIED
41031	AMI INFEROPOST, INITIAL	41081	AMI NEC, INITIAL
41040	AMI INFERIOR WALL, UNSPEC	41090	AMI NOS, UNSPECIFIED
41041	AMI INFERIOR WALL, INIT	41091	AMI NOS, INITIAL

Denominator exclusions

Exclude cases:

- transferring to another short-term hospital (DISP=2)
- MDC 14 (pregnancy, childbirth, and puerperium
- with missing discharge disposition (DISP=missing), gender (SEX=missing), age (AGE=missing), quarter (DQTR=missing), year (YEAR=missing), or principal diagnosis (DX1=missing)

Sources: AHRQ Quality Indicators™ Program; Agency for Healthcare Research and Quality (2017a). https://www.qualityindicators.ahrq.gov/Downloads/Modules/IQI/V60/TechSpecs/IQI_15_Acute_Myocardial_Infarction (AMI)_Mortality_Rate.pdf.

Table 11A.2 AMI inpatient mortality risk model

Parameter	Label	Estimate	Standard error	Wald chi-square	Pr > chi-square
Intercept	Intercept	–3.6765	0.4222	75.8134	<.0001
M_AgeCat_6	Male | Age < 55	–0.2537	0.0397	40.8156	<.0001
M_AgeCat_8	Male | Age < 65	0.0759	0.035	4.697	0.0302
M_AgeCat_9	Male | Age >= 65	0.0768	0.0328	5.4625	0.0194
M_AgeCat_11	Male | Age >= 75	0.1591	0.0282	31.798	<.0001
M_AgeCat_13	Male | Age >= 85	0.1453	0.0348	17.4855	<.0001
M_AgeCat_14	Male | Age >= 90	0.1218	0.0448	7.3979	0.0065
F_AgeCat_6	Female | Age < 55	–0.1659	0.0597	7.7307	0.0054
F_AgeCat_8	Female | Age < 65	–0.0325	0.0431	0.5659	0.4519
F_AgeCat_11	Female | Age >= 75	0.1075	0.0335	10.3035	0.0013
F_AgeCat_13	Female | Age >= 85	0.1112	0.0346	10.3116	0.0013
F_AgeCat_14	Female | Age >= 90	0.2911	0.0377	59.7157	<.0001
MDC_5	MDC 5: DISEASES & DISORDERS OF THE CIRCULATORY SYSTEM	2.1557	0.4199	26.3579	<.0001
ADX161_0001	DRG 161: Cardiac defibrillator & heart assist implant	–1.6775	0.5909	8.058	0.0045
ADX161_0002	DRG 161: Cardiac defibrillator & heart assist implant	–1.7192	0.2372	52.5474	<.0001
ADX161_0003	DRG 161: Cardiac defibrillator & heart assist implant	–1.512	0.129	137.3374	<.0001
ADX161_0004	DRG 161: Cardiac defibrillator & heart assist implant	0.5553	0.0607	83.5733	<.0001
ADX162_0003	DRG 162: Cardiac valve procedures w cardiac catheterization	–1.9697	0.2068	90.7299	<.0001
ADX162_0012	DRG 162: Cardiac valve procedures w cardiac catheterization	–3.5914	0.5804	38.2825	<.0001
ADX163_0003	DRG 163: Cardiac valve procedures w/o cardiac catheterization	–2.286	0.4544	25.3048	<.0001
ADX163_0012	DRG 163: Cardiac valve procedures w/o cardiac catheterization	–2.357	0.5852	16.2216	<.0001
ADX165_0003	DRG 165: Coronary bypass w cardiac cath or percutaneous cardiac procedure	–2.7485	0.0899	934.1475	<.0001
ADX165_0004	DRG 165: Coronary bypass w cardiac cath or percutaneous cardiac procedure	–0.7461	0.0585	162.5885	<.0001
ADX165_0012	DRG 165: Coronary bypass w cardiac cath or percutaneous cardiac procedure	–4.5302	0.1782	646.075	<.0001
ADX166_0003	DRG 166: Coronary bypass w/o cardiac cath or percutaneous cardiac procedure	–2.9037	0.1974	216.3155	<.0001
ADX166_0004	DRG 166: Coronary bypass w/o cardiac cath or percutaneous cardiac procedure	–0.5389	0.1036	27.0435	<.0001
ADX166_0012	DRG 166: Coronary bypass w/o cardiac cath or percutaneous cardiac procedure	–5.2789	0.5018	110.6855	<.0001
ADX167_0004	DRG 167: Other cardiothoracic procedures	0.8715	0.296	8.6713	0.0032
ADX167_0123	DRG 167: Other cardiothoracic procedures	–0.9615	0.4683	4.2156	0.0401
ADX169_0002	DRG 169: Major thoracic & abdominal vascular procedures	–2.3345	1.0119	5.322	0.0211
ADX169_0003	DRG 169: Major thoracic & abdominal vascular procedures	–1.6476	0.5915	7.7588	0.0053
ADX169_0004	DRG 169: Major thoracic & abdominal vascular procedures	0.8006	0.226	12.5455	0.0004
ADX170_0003	DRG 170: Permanent cardiac pacemaker implant w AMI heart failure or shock	–2.4126	0.2732	77.9654	<.0001

(*continued*)

Table 11A.2 (cont.)

Parameter	Label	Estimate	Standard error	Wald chi-square	Pr > chi-square
ADX173_0003	DRG 173: Other vascular procedures	–1.599	0.2082	58.9771	<.0001
ADX173_0004	DRG 173: Other vascular procedures	0.6323	0.1469	18.5311	<.0001
ADX173_0012	DRG 173: Other vascular procedures	–1.7646	0.5897	8.9546	0.0028
ADX174_0001	DRG 174: Percutaneous cardiovascular procedures w AMI	–5.4385	0.1131	2313.699	<.0001
ADX174_0002	DRG 174: Percutaneous cardiovascular procedures w AMI	–4.1135	0.0717	3291.108	<.0001
ADX174_0003	DRG 174: Percutaneous cardiovascular procedures w AMI	–2.288	0.0532	1847.254	<.0001
ADX174_0004	DRG 174: Percutaneous cardiovascular procedures w AMI	0.2224	0.0405	30.1245	<.0001
ADX175_0001	DRG 175: Percutaneous cardiovascular procedures w/o AMI	–4.6469	1.0018	21.5166	<.0001
ADX175_0002	DRG 175: Percutaneous cardiovascular procedures w/o AMI	–2.7821	0.5828	22.7908	<.0001
ADX175_0003	DRG 175: Percutaneous cardiovascular procedures w/o AMI	–1.3744	0.3915	12.3253	0.0004
ADX176_0034	DRG 176: Cardiac pacemaker & defibrillator device replacement	–1.727	0.7246	5.6799	0.0172
ADX180_0003	DRG 180: Other circulatory system procedures	–1.2703	0.3138	16.3888	<.0001
ADX180_0012	DRG 180: Other circulatory system procedures	–2.3913	0.7158	11.1597	0.0008
ADX190_0001	DRG 190: Acute myocardial infarction	–4.2908	0.1255	1168.52	<.0001
ADX190_0002	DRG 190: Acute myocardial infarction	–2.8623	0.0588	2367.434	<.0001
ADX190_0003	DRG 190: Acute myocardial infarction	–1.3875	0.0403	1185.963	<.0001
ADX190_0004	DRG 190: Acute myocardial infarction	0.7259	0.0393	340.8797	<.0001
ADX191_0001	DRG 191: Cardiac catheterization w circ disord exc ischemic heart disease	–3.1417	1.0053	9.7658	0.0018
ADX191_0002	DRG 191: Cardiac catheterization w circ disord exc ischemic heart disease	–3.2554	1.0052	10.4873	0.0012
ADX198_0001	DRG 198: Angina pectoris & coronary atherosclerosis	–1.2529	0.3681	11.5852	0.0007
ADX198_0002	DRG 198: Angina pectoris & coronary atherosclerosis	–1.0658	0.2262	22.1947	<.0001
ADX198_0003	DRG 198: Angina pectoris & coronary atherosclerosis	–0.4057	0.1769	5.2596	0.0218
TRNSFER	Transfer Status	0.0294	0.0211	1.9368	0.164

Sources: AHRQ Quality Indicators™ Program; Agency for Healthcare Research and Quality (2017b, p. 19–21). https://www.qualityindicators.ahrq.gov/Downloads/Modules/IQI/V60/Parameter_Estimates_IQI_6.0_ICD-9-CM.pdf

Table 11A.3 **Complete results from baseline regressions**

Episode type	Heart attack	Heart failure	Pneumonia	GI bleed
Coefficient (standard error)				
Constant	–8.618***	–1.571**	5.581***	2.195***
	(0.628)	(0.701)	(0.653)	(0.600)
2003 episode	–0.030***	–0.045***	–0.003	–0.035***
	(0.011)	(0.010)	(0.010)	(0.013)
2004 episode	–0.058***	–0.098***	–0.023**	–0.053***
	(0.012)	(0.010)	(0.010)	(0.012)
2005 episode	–0.065***	–0.132***	–0.023**	–0.065***
	(0.012)	(0.011)	(0.010)	(0.013)
2006 episode	–0.044***	–0.116***	–0.015	–0.063***
	(0.013)	(0.011)	(0.010)	(0.013)
2007 episode	0.001	–0.104***	0.001	–0.033**
	(0.013)	(0.013)	(0.011)	(0.014)
2008 episode	–0.021	–0.166***	–0.044***	–0.115***
	(0.013)	(0.015)	(0.012)	(0.014)
2009 episode	0.011	–0.151***	–0.030**	–0.072***
	(0.013)	(0.017)	(0.012)	(0.014)
2010 episode	0.015	–0.172***	–0.036***	–0.093***
	(0.013)	(0.018)	(0.012)	(0.014)
2011 episode	0.033**	–0.139***	–0.002	–0.060***
	(0.014)	(0.019)	(0.012)	(0.015)
2012 episode	0.088***	–0.095***	0.042***	–0.037**
	(0.014)	(0.020)	(0.013)	(0.015)
2013 episode	0.060***	–0.121***	0.038***	–0.073***
	(0.014)	(0.020)	(0.013)	(0.014)
2014 episode	0.104***	–0.053**	0.086***	–0.010
	(0.017)	(0.023)	(0.015)	(0.017)
AHRQ predicted inpatient survival, logged	3.043***	8.184***	6.968***	7.215***
	(0.089)	(0.317)	(0.175)	(0.185)
Location of heart attack: Anterolateral (410.0x)	–0.416***	—	—	—
	(0.082)			
Location of heart attack: Other anterior wall (410.1x)	–0.354***	—	—	—
	(0.052)			
Location of heart attack: Inferolateral wall (410.2x)	–0.083	—	—	—
	(0.084)			
Location of heart attack: Inferoposterior wall (410.3x)	–0.505***	—	—	—
	(0.103)			
Location of heart attack: Other inferior wall (410.4x)	–0.350***	—	—	—
	(0.051)			
Location of heart attack: Other lateral wall (410.5x)	–0.205**	—	—	—
	(0.095)			
Location of heart attack: True posterior wall (410.6x)	–0.508***	—	—	—
	(0.184)			
Location of heart attack: Sub–endocardial (410.7x)	–0.164***	—	—	—
	(0.037)			
Location of heart attack: Other specified sites (410.8x)	–0.273***	—	—	—
	(0.080)			
Location of heart attack: Unspecified site (410.9x)	—	—	—	—

(continued)

Table 11A.3 **(cont.)**

Episode type	Heart attack	Heart failure	Pneumonia	GI bleed
No Charlson-Deyo comorbidities	—	—	—	—
1 Charlson-Deyo comorbidity	0.369***	0.101	–0.126***	–0.167***
	(0.041)	(0.179)	(0.031)	(0.026)
2 Charlson-Deyo comorbidities	0.198***	–0.018	–0.338***	–0.464***
	(0.039)	(0.183)	(0.031)	(0.029)
3 Charlson-Deyo comorbidities	0.086**	–0.129	–0.524***	–0.601***
	(0.042)	(0.182)	(0.040)	(0.037)
4 Charlson-Deyo comorbidities	0.027	–0.245	–0.578***	–0.722***
	(0.047)	(0.184)	(0.055)	(0.046)
5+ Charlson-Deyo comorbidities	—	–0.325*	–1.032***	–1.059***
		(0.185)	(0.062)	(0.051)
Age, logged	0.734***	-0.356***	–2.007***	–1.208***
	(0.105)	(0.123)	(0.110)	(0.102)
Female	0.037*	–0.038	–0.092***	–0.043**
	(0.022)	(0.024)	(0.022)	(0.021)
White	0.176***	0.258***	0.140**	0.121**
	(0.061)	(0.063)	(0.059)	(0.048)
African American	0.146**	0.243***	–0.117*	–0.088
	(0.068)	(0.066)	(0.068)	(0.055)
Hispanic	0.678***	0.771***	0.516***	0.399***
	(0.105)	(0.114)	(0.114)	(0.093)
Other race	—	—	—	—
1st quarter of year episode	—	—	—	—
2nd quarter of year episode	0.033	–0.013	0.006	0.034
	(0.028)	(0.031)	(0.028)	(0.026)
3rd quarter of year episode	0.014	–0.074**	–0.137***	–0.022
	(0.030)	(0.031)	(0.030)	(0.026)
4th quarter of year episode	–0.009	–0.006	–0.021	–0.036
	(0.030)	(0.032)	(0.030)	(0.026)
Patient zip code characteristics				
Median household income ($000)	–0.006***	–0.010***	–0.007***	–0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Social Security income ($000)	–0.006	–0.018*	–0.019**	–0.022***
	(0.009)	(0.010)	(0.009)	(0.008)
Poor	0.569**	–0.459*	0.293	0.239
	(0.252)	(0.242)	(0.226)	(0.226)
Employed	2.105***	0.573*	1.179***	1.228***
	(0.397)	(0.345)	(0.371)	(0.336)
Less than high school education	–0.004	–0.188	–0.604***	–0.453***
	(0.155)	(0.143)	(0.130)	(0.126)
Urban	–0.086**	–0.123***	–0.138***	–0.141***
	(0.036)	(0.035)	(0.030)	(0.032)
Hispanic	–0.581***	–0.593***	–0.574***	–0.517***
	(0.062)	(0.065)	(0.059)	(0.057)
Single	–0.757***	–0.702***	–0.530***	–0.732***
	(0.158)	(0.154)	(0.149)	(0.150)
Elderly in an institution	–0.034	0.547***	–0.173	0.206
	(0.200)	(0.209)	(0.189)	(0.166)

Table 11A.3 (cont.)

Episode type	Heart attack	Heart failure	Pneumonia	GI bleed
Noninstitutionalized elderly with physical disability	0.385*	0.236	–0.137	–0.077
	(0.221)	(0.239)	(0.219)	(0.200)
Mental disability	–0.494	–0.731**	–0.345	–0.049
	(0.338)	(0.325)	(0.308)	(0.279)
Sensory disability among elderly	0.056	–0.008	0.537*	–0.095
	(0.296)	(0.332)	(0.296)	(0.276)
Self-care disability	–0.214	0.445	0.375	0.020
	(0.393)	(0.364)	(0.369)	(0.360)
Difficulty going-outside-the-home disability	–0.124	–0.353	–0.760***	–0.267
	(0.271)	(0.269)	(0.257)	(0.253)
Index hospital characteristics				
Residents per bed = 0	—	—	—	—
Residents per bed > 0 and ≤ 0.25	–0.077***	–0.071***	–0.009	–0.049***
	(0.011)	(0.011)	(0.010)	(0.010)
Residents per bed > 0.25 and ≤ 0.6	–0.158***	–0.173***	–0.087***	–0.167***
	(0.020)	(0.022)	(0.021)	(0.021)
Residents per bed > 0.6	–0.181***	–0.211***	–0.055*	–0.188***
	(0.027)	(0.027)	(0.033)	(0.035)
Other statistics				
Hospital-years, *n*	28,635	39,650	40,735	36,804
R^2	0.191	0.227	0.268	0.243

Episode type	Hip fracture	Stroke	LEJR	COPD
Coefficient (standard error)				
Constant	4.473***	5.085***	2.131***	0.337
	(0.565)	(0.585)	(0.703)	(0.599)
2003 episode	–0.010	–0.012	–0.014*	0.008
	(0.012)	(0.015)	(0.008)	(0.012)
2004 episode	–0.033***	–0.039***	–0.024***	0.011
	(0.012)	(0.015)	(0.008)	(0.012)
2005 episode	–0.032***	–0.043***	–0.019**	0.015
	(0.012)	(0.015)	(0.008)	(0.012)
2006 episode	–0.069***	–0.032**	–0.022***	0.011
	(0.012)	(0.015)	(0.008)	(0.012)
2007 episode	–0.116***	–0.061***	–0.028***	0.038***
	(0.014)	(0.015)	(0.009)	(0.013)
2008 episode	–0.102***	–0.038**	–0.044***	–0.051***
	(0.012)	(0.015)	(0.009)	(0.013)
2009 episode	–0.099***	–0.023	–0.036***	–0.040***
	(0.012)	(0.016)	(0.009)	(0.013)
2010 episode	–0.111***	–0.023	–0.050***	–0.033**
	(0.013)	(0.015)	(0.009)	(0.013)
2011 episode	–0.096***	0.002	–0.030***	–0.010
	(0.012)	(0.015)	(0.009)	(0.013)
2012 episode	–0.045***	0.075***	0.004	0.054***
	(0.013)	(0.015)	(0.009)	(0.013)

(*continued*)

Table 11A.3 (cont.)

Episode type	Hip fracture	Stroke	LEJR	COPD
2013 episode	–0.010	0.062***	0.051***	0.092***
	(0.013)	(0.015)	(0.009)	(0.013)
2014 episode	0.014	0.125***	0.078***	0.139***
	(0.015)	(0.018)	(0.011)	(0.015)
AHRQ predicted inpatient survival, logged	3.266***	4.141***	—	—
	(0.141)	(0.123)		
Location of heart attack: Anterolateral (410.0x)	—	—	—	—
Location of heart attack: Other anterior wall (410.1x)	—	—	—	—
Location of heart attack: Inferolateral wall (410.2x)	—	—	—	—
Location of heart attack: Inferoposterior wall (410.3x)	—	—	—	—
Location of heart attack: Other inferior wall (410.4x)	—	—	—	—
Location of heart attack: Other lateral wall (410.5x)	—	—	—	—
Location of heart attack: True posterior wall (410.6x)	—	—	—	—
Location of heart attack: Sub-endocardial (410.7x)	—	—	—	—
Location of heart attack: Other specified sites (410.8x)	—	—	—	—
Location of heart attack: Unspecified site (410.9x)	—	—	—	—
No Charlson-Deyo comorbidities	—	—	—	—
1 Charlson-Deyo comorbidity	–0.171***	0.788***	–0.122***	0.696***
	(0.018)	(0.036)	(0.018)	(0.051)
2 Charlson-Deyo comorbidities	–0.283***	0.621***	–0.294***	0.437***
	(0.023)	(0.037)	(0.029)	(0.052)
3 Charlson-Deyo comorbidities	–0.389***	0.318***	–0.406***	0.289***
	(0.033)	(0.037)	(0.047)	(0.055)
4 Charlson-Deyo comorbidities	–0.454***	0.159***	–0.545***	0.180***
	(0.054)	(0.040)	(0.075)	(0.062)
5+ Charlson-Deyo comorbidities	–0.418***	—	—	—
	(0.061)			
Age, logged	–1.819***	–1.970***	–1.667***	–0.909***
	(0.084)	(0.101)	(0.103)	(0.108)
Female	0.043**	–0.133***	–0.062***	–0.115***
	(0.018)	(0.020)	(0.018)	(0.020)
White	0.116**	0.278***	0.199***	0.225***
	(0.047)	(0.056)	(0.054)	(0.055)
African American	–0.079	0.072	–0.006	0.086
	(0.060)	(0.062)	(0.068)	(0.062)
Hispanic	0.531***	0.823***	0.508***	0.613***
	(0.084)	(0.110)	(0.126)	(0.102)
Other race	—	—	—	—
1st quarter of year episode	—	—	—	—
2nd quarter of year episode	0.015	0.013	–0.020	–0.029
	(0.022)	(0.027)	(0.021)	(0.024)

Table 11A.3 (cont.)

Episode type	Hip fracture	Stroke	LEJR	COPD
3rd quarter of year episode	–0.001	0.025	–0.053**	–0.098***
	(0.020)	(0.027)	(0.020)	(0.028)
4th quarter of year episode	–0.018	0.006	–0.048**	–0.006
	(0.022)	(0.028)	(0.022)	(0.026)
Patient zip code characteristics				
Median household income ($000)	–0.005***	–0.005***	–0.007***	–0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Social Security income ($000)	–0.009	–0.014	0.004	–0.022**
	(0.007)	(0.009)	(0.009)	(0.009)
Poor	0.552***	0.072	0.639***	–0.109
	(0.180)	(0.248)	(0.227)	(0.216)
Employed	–0.125	0.207	0.472	1.062***
	(0.287)	(0.353)	(0.363)	(0.340)
Less than high school education	–0.424***	–0.322**	–0.571***	–0.186
	(0.113)	(0.144)	(0.130)	(0.139)
Urban	–0.150***	–0.155***	–0.050	–0.115***
	(0.026)	(0.035)	(0.034)	(0.031)
Hispanic	–0.552***	–0.654***	–0.482***	–0.677***
	(0.048)	(0.062)	(0.065)	(0.066)
Single	–0.483***	–0.698***	–0.804***	–0.695***
	(0.111)	(0.154)	(0.151)	(0.156)
Elderly in an institution	–0.172	0.093	0.375**	0.203
	(0.133)	(0.164)	(0.171)	(0.172)
Noninstitutionalized elderly with physical disability	–0.134	–0.015	–0.236	0.282
	(0.163)	(0.213)	(0.192)	(0.221)
Mental disability	–0.325	0.013	0.046	–0.781***
	(0.235)	(0.317)	(0.265)	(0.296)
Sensory disability among elderly	0.204	–0.070	0.045	0.152
	(0.200)	(0.264)	(0.233)	(0.288)
Self-care disability	0.319	–0.510	0.157	–0.130
	(0.271)	(0.368)	(0.312)	(0.340)
Difficulty going-outside-the-home disability	–0.268	0.001	0.124	–0.352
	(0.191)	(0.251)	(0.234)	(0.258)
Index hospital characteristics				
Residents per bed = 0	—	—	—	—
Residents per bed > 0 and ≤ 0.25	–0.021**	–0.068***	0.017*	–0.047***
	(0.009)	(0.011)	(0.010)	(0.011)
Residents per bed > 0.25 and ≤ 0.6	–0.057***	–0.154***	0.003	–0.124***
	(0.018)	(0.022)	(0.019)	(0.022)
Residents per bed > 0.6	–0.055*	–0.211***	–0.041	–0.092***
	(0.030)	(0.027)	(0.026)	(0.033)
Other statistics				
Hospital-years, *n*	29,800	32,006	34,073	39,478
R^2	0.170	0.248	0.326	0.166

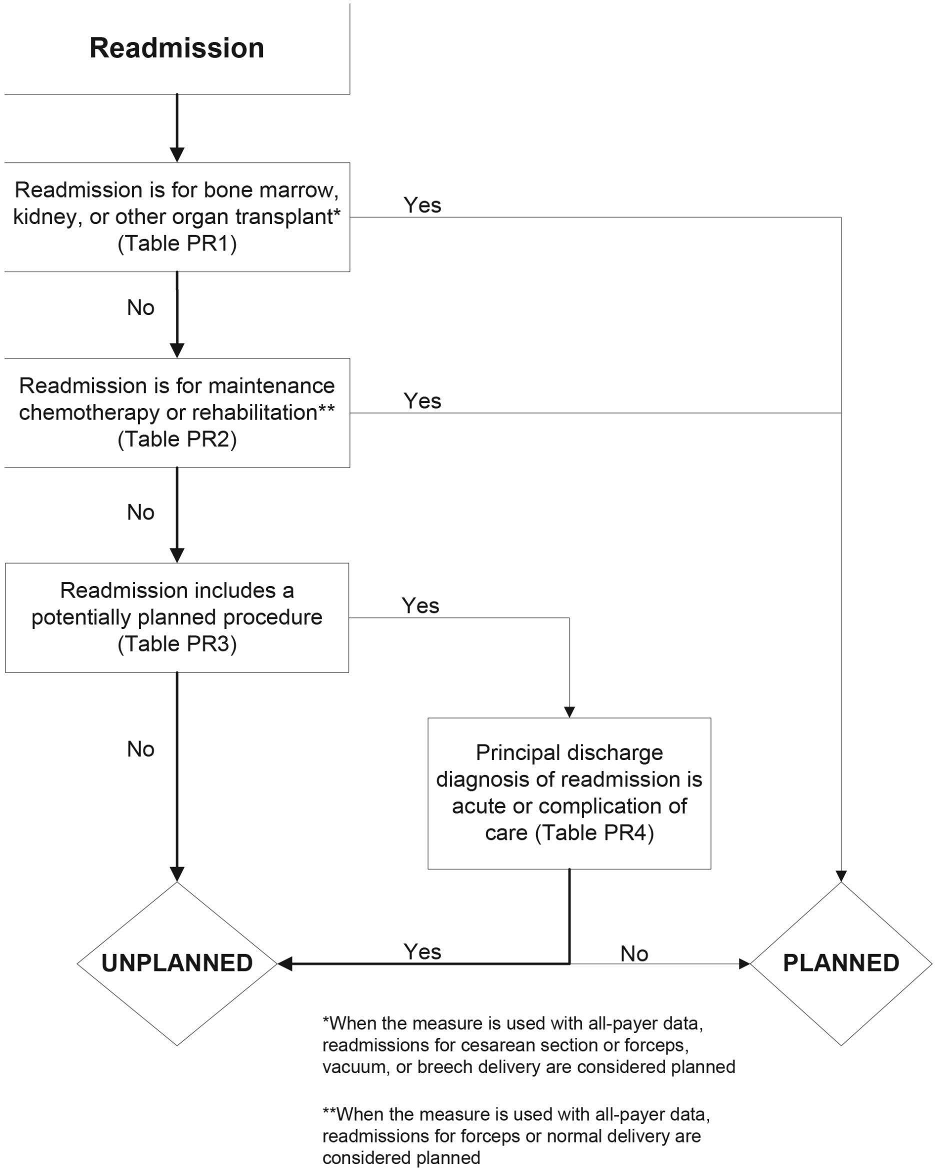


Fig. 11A.1 Overview of CMS unplanned readmission algorithm

Source: Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation (YNHHSC/CORE 2014, 64).

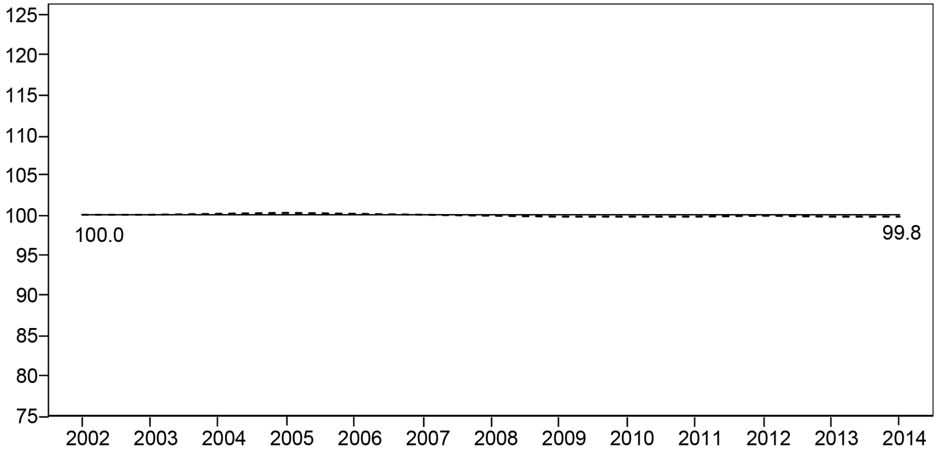


Fig. 11A.2 Other hospital production index among heart-attack episodes

Note: We construct the patient severity index by exponentiating $-\bar{O}_{ht}\hat{\beta}_O$, obtaining $\hat{\beta}_O$ from the regression results corresponding to Figures 16 and 17 and normalizing the index to a value of 100 in 2002.

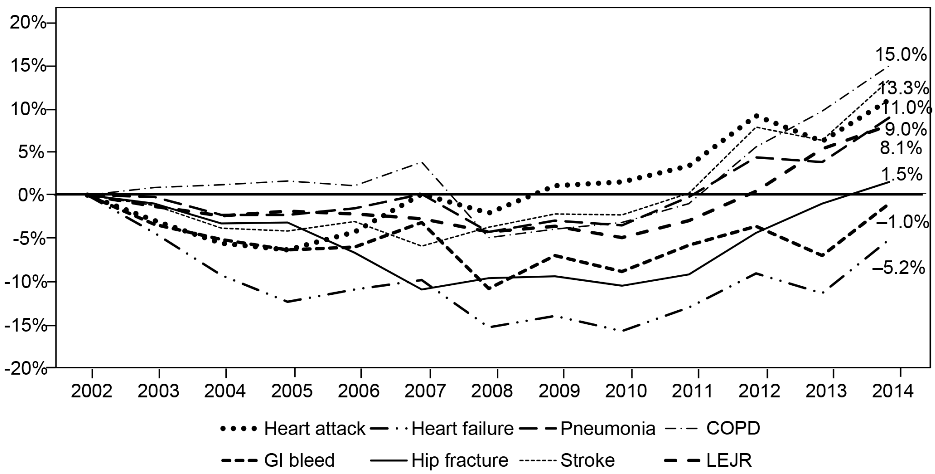


Fig. 11A.3 Cumulative change in productivity since 2002

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