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

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We assess changes in multifactor productivity in delivering acute episodes of care (including services received after initial discharge from a hospital) for elderly Medicare beneficiaries over 2002-2014. For a majority of the eight episode types studied, productivity improved, exceeding an annualized growth rate of 1.0% in some cases. There is some evidence of negative productivity growth for heart failure episodes over this period. Our estimates reflect ─ and are meaningfully affected by the measurement of ─ trends in the quality of care, with patients experiencing improved outcomes for most episode types.

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 et al. 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 mis-measured MFP improvement, in fact understating it.(Feldstein 2017) Recent assessments cast some doubt on this alternative view as a convincing account of the apparent slowdown in productivity growth.(Byrne, Fernald et al. 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, Hartman 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 mis-measurement of health care inflation was a key concern of the Boskin Commission.(Boskin, Dulberger et al. 1998) Indeed, taking account of improved outcomes, the price of heart attack treatment has actually declined markedly over time.(Cutler, McClellan 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, Newhouse 1992, Baumol, de Ferranti et al. 2012) 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,

Khandrika 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.(Cylus and Dickensheets 2007, Groshen, Moyer 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 U.S. 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 et al. 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 productive, 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.[1] For

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[1]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 price measurement based on an episode of care.

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 time frame (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.

2. Approach

　　　The starting point for our analysis is CMS's Inpatient Files.(Research Data Assistance

Center) Our version of the Inpatient Files includes a random 20% sample of Medicare

beneficiaries. As Table 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 1 provides an overview of the CMS

algorithm. Publicly available code produces a stay-level data set by combining associated claims.

One of the episode types we study is acute myocardial infarction (AMI), or heart attack. Table 1 shows that 811,517 stays at 5,510 hospitals were 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)

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 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:

$$\ln(Y_{ht}/C_{ht}) = \alpha + \boldsymbol{S_{ht}}\boldsymbol{\beta_S} + \boldsymbol{O_{ht}}\boldsymbol{\beta_O} + g(t) + \epsilon_{ht},$$

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.(Romley, Goldman et al. 2015, Sheiner and Malinovskaya 2016, Gu, Sood et al. 2019, Romley, Trish et al. 2019)

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 by "high-quality" episodes. Under this framework, the health care system does not receive full credit (in terms of output) for a 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 high-quality inpatient stays.(Romley, Goldman et al. 2015, Romley, Trish 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 tradeoff 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.[2] 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 of discharge. Both of 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 2019f, Centers for Medicare and Medicaid Services 2019e) 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 of our episode types. In this study, we continue to use these outcomes. For example, as Table 1 reports, 558,999 AMI stays at 5,290 hospitals met all of 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.[3] 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."[4] Age and enrollment are

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[2](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 qualiity 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.

[3]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.

[4]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.

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 addition to survival without an unplanned readmission, our quality composite 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.)[5]

In prior studies, our composite rate of high-quality outcomes specified that every outcome be favorable. Thus, a patient who died experienced a low-quality stay, and a patient with a readmission also experienced a low-quality stay, and to an equal degree. This specification, while simple, seems 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).

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

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

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 re-scale 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.

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[6], in contrast with the "cost of living" approach.(Sheiner and Malinovskaya 2016) The latter was used to develop the heart attack inflation measure referenced previously.(Cutler, McClellan 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 et al. 2019) shows that a cost of living index indicates greater improvement than our approach here when the value of the health improvement exceeds its incremental cost[7], 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, Khandrika 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, Doyle 2011, Skinner and Staiger 2015, Chandra, Finkelstein et al. 2016)), aggregating all episodes of each type at each index hospital-year. To do so, we identify

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[6]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 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.)

[7]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 et al. 2019).

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.[8] The Carrier File of professional claims was the largest of these; in the 2014 File, the 20% 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 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.[9]

CCRs are sometimes unavailable, and our primary analysis excludes episodes for which any CCR is missing. As Table 1 shows, this criterion excludes about 15% of heart-attack

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[8]These types of claims correspond to the Inpatient, Outpatient, Carrier, Skilled Nursing Facility, Home Health Agency, Durable Medical Equipment, and Hospice Files, respectively.
[9]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)

episodes. In a sensitivity analysis, we also include episodes with 1 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 was less than or equal to the median for the

episode type.[10] 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

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[10]We include payments from all sources.

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) We inflation-adjust professional costs by reversing the

productivity adjustments to the MEI; durable medical equipment costs are similarly deflated.

Turning to patient severity (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 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. We

use the average predicted likelihood of survival beyond the hospitalization, derived from these

models, averaged across episodes initiated at an index hospital in a year. Table 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

mortality for the sake of clinical specificity. Details of the IQI inclusion / exclusion criteria for

heart-attack episodes are shown in Appendix Figure 2.

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 Appendix Figure 3.

We further 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, Pompei et al. 1987, Quan, Sundararajan 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 et al. 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, Goodman et al. 2005, Cox, Stone 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, Wennberg et al. 2003a, Fisher, Wennberg et al. 2003b, Romley, Jena et al. 2011, Romley, Goldman et al. 2015); examples include the poverty rate and the proportion of elderly residents with self-care limitations. As Table 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, Rosen et al. 2007); this data is 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 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 1 shows that 2.7% of AMI episodes treated at 8.0% 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 into 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.

3. Findings

Before reviewing our regression results, we first describe the episodes studied, with a focus on AMI, that is, heart attack. Table 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. 79.4% of elderly Medicare beneficiaries admitted to a hospital with a heart attack survived at least 90 days beyond the initial discharge. The AHRQ AMI IQI predicts that 92.2% would have survived beyond the initial hospital stay. Among 90-day survivors, 85.1% avoided an unplanned readmission within 30 days of initial discharge. Among survivors without a readmission, 81.6% 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 very simple measure of productivity is the cost of a heart-attack episode, irrespective of patient severity or outcomes. Figure 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 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%).

In 2014, the total cost of all of these episodes was $38.3 billion, measured in 2014

dollars.[11] Focusing on the 3 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 3 episode types was $7.8 billion. For

heart attack alone, the total cost of initial hospital stays in 2014 was $2.8 billion.

The simple measures shown in the top panel of Figure 2 ignore the quality of the health

outcomes delivered to patients. Figure 3 shows that survival improved for heart-attack patients,

rising from a rate of 77.8% in 2002 to a rate of 82.8% in 2014. Among survivors, the rate of

avoidance of unplanned readmission within 30 days of initial discharge improved from 83.5% to

86.8%. The rate of discharge to home from the last facility claim declined somewhat, from

84.4% in 2002 to 83.4% in 2014.

Defining a high-quality episode as survival without institutionalization (whether an

unplanned readmission or a discharge to another facility), Figure 3 shows that the rate of high-

quality episodes increased from 55.7% in 2002 to 60.8% in 2014 for heart-attack patients. The

middle panel of Figure 2 shows the rate of high-quality episodes for all episode types. This rate

improved for 6 of the 8 episode types; the increase was greatest in absolute terms for hip fracture

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[11]Total costs in our analytic sample were multiplied by a factor of five, because we had access to a 20% 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.)

(5.8 percentage points) and in relative terms for LEJR (18.7%). The rate of high-quality stays declined by 3.6 percentage points for heart failure episodes. Among these patients, avoidance of readmission got better, but survival and home discharge rates got worse.

Figure 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. Figure 2 shows the cost of high-quality episodes for all episode types. This cost increased for 5 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%). 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%, respectively.)

These changes in the cost of a high-quality episode may have reflected trends in the severity of patients treated. Figure 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 2.62 in 2014. The predicted likelihood of inpatient survival from the AHRQ IQI risk model decreased from 93.3% to 92.8% over the period.

Using all of our patient severity measure and the results of our primary regressions, we can construct a patient severity index.[12] For heart-attack episodes, Figure 5 shows that severity

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[12]The construction of the index is described in the note to Figure 105.

increased from its baseline value of 100 in 2002, starting to rise more rapidly in 2007 and reaching a peak of 110.0 in 2010, then settling at 103.1 in 2014. This pattern means that the heart-attack patients treated in 2014 would have required 3.1% higher costs to enjoy the same outcomes as patients in 2002. Figure 6 shows the 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 4 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 7. Productivity declined at first, reaching a trough of -6.3% cumulative growth since 2002, before beginning to improve fairly consistently, reaching a maximum of 11.0% improvement (over 2002) by 2014. A similar pattern was observed in our prior studies of hospital and nursing home stays.(Romley, Goldman et al. 2015, Gu, Sood et al. 2019) The productivity trajectories for all episode types are shown in Appendix Figure 5; complete regression results are reported in the Appendix Table.[13]

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[13]In general, the regression coefficients have the expected signs. For the 6 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 one percent increase (relative, not absolute) in the average survival probability of stroke patients is associated with 4.1% more stays or better outcomes (given costs), or 4.1% lower costs (given the number of episodes and their quality.) Likewise, having fewer Charlson-Deyo co-morbidities recorded on the initial hospital record is associated with greater output or lower costs. For LEJR, for example, if all patients had no comorbidities rather than one comorbidity, output would be roughly 12% greater, or costs 12% lower. Finally, for all episode types except heart attack, a younger patient population is associated with more output or lower costs. For pneumonia, for example, a one percent decrease in average age is associated with 2.1% more output or lower costs.

On an annualized basis, productivity for heart-attack episodes grew by 0.87% on average between 2002 and 2014. Figure 8 shows somewhat slower growth for pneumonia and LEJR, but even great improvement (in excess of 1.0% 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% per year on average.

Figure 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% versus 1.37% 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% with versus +0.62% 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% per year when quality is ignored, versus 1.17% per year otherwise. For heart failure, quality adjustment results in somewhat more negative growth (-0.44% per year versus -0.30% per year), because quality declined in the aggregate.

The results thus far assume that institutionalization (whether unplanned readmission of discharge to another facility) causes a decrease in quality of life of -0.66. That is, survival with institutionalization is 34% as good as survival without institutionalization. As noted previously, there is substantial uncertainty about the impact of institutionalization on quality of life. Figure 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% per year, instead of 0.87% with the baseline intermediate value. With a decrement of 1.0, growth is higher, namely, 1.06% per year. For hip fracture, the baseline estimate is an insignificant +0.12% per year, but significant at +0.78% and -0.23% 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 -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 et al. 2015, Gu, Sood et al. 2019, Romley, Trish et al. 2019) With this alternative value, a 10% percent improvement in quality requires a 10% decrease in the number of episodes, instead of 14% according to the baseline value. Consequently, measured productivity growth, given a favorable quality trend, is slower under this alternative value. Figure 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% per year becomes a marginally significant decline of 0.20% per year.

As noted previously, cost data is unavailable for some facility claims (15% of heart-attack episodes had at least 1 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 total payments for such episodes in each year. Figure 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 13 shows, measured productivity growth 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% per year.

Based on our baseline results, composite productivity growth, aggregated across all episode types, is shown in Figure 14. The growth rate is +0.44% per year on average over 2002-2014 when productivity is aggregated based on cost shares using 2002 shares as the base, and +0.45% and +0.44% when using cost shares from2008 and 2014, respectively.

4. Conclusion

There is widespread concern about poor coordination in U.S. 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 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 one 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.

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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%. The cost of care provided under Medicare Parts A and B for these episodes totaled $38 billion in in 2014, measured in 2014 dollars, compared to overall program spending of $367 billion.(Cubanski, Neuman et al. 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, Bir et al. 2002) has already considered depression, while (Eggleston, Shah et al. 2011) has addressed 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% per year when we account for quality of care, but -0.29% 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, McClellan 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 et al. 2016, Dunn, Whitmire 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.

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Table 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

Table 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)
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%)
Non-institutionalized 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%)

Figure 1:
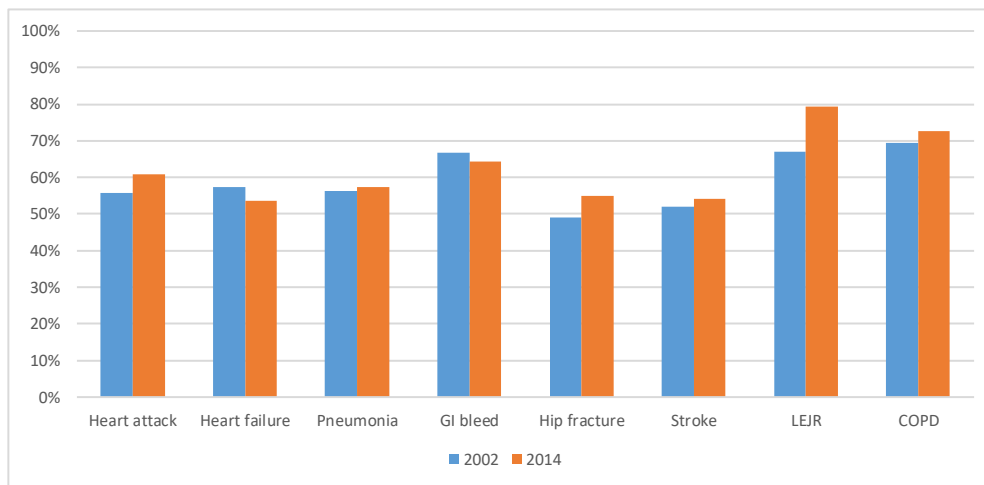**Cost of Heart-Attack Episodes (000s of 2014 Dollars)**
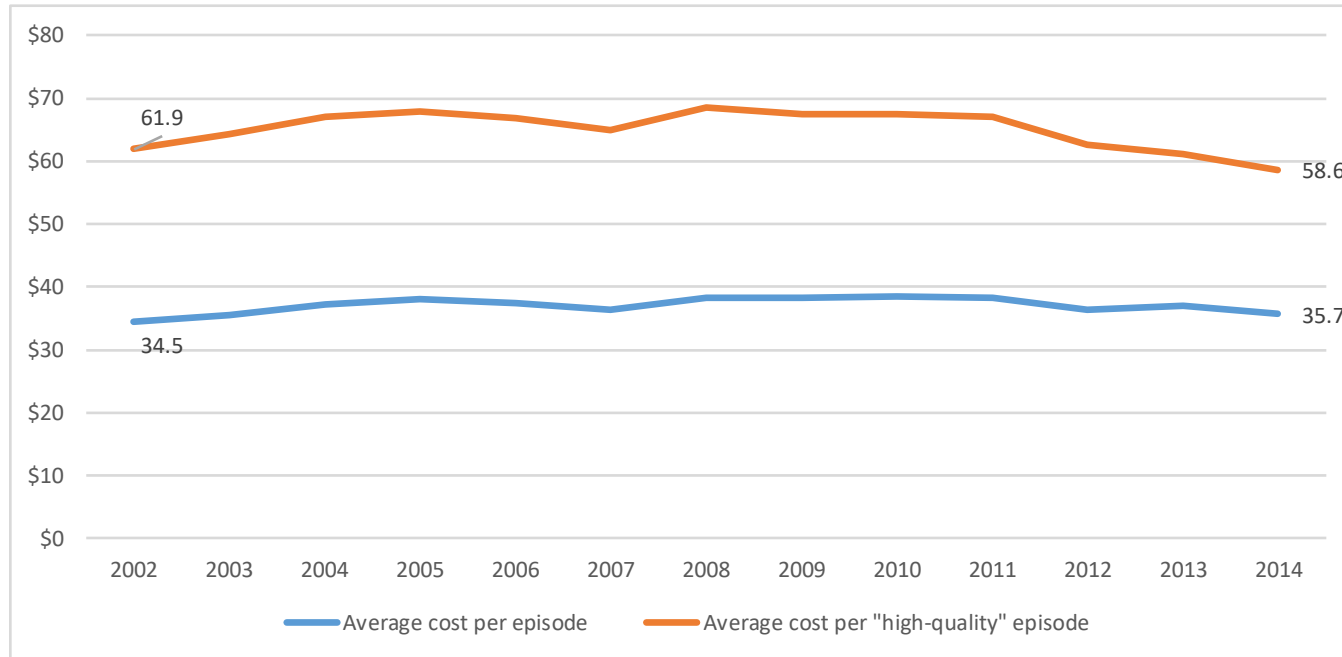
Notes: In this figure, a "high-quality" episode means that the patient survived through the end of the episode, avoided an unplanned readmission within 30 days of the initial discharge, and was discharged home from the last facility claim. This definition corresponds to a quality of life decrement for 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.
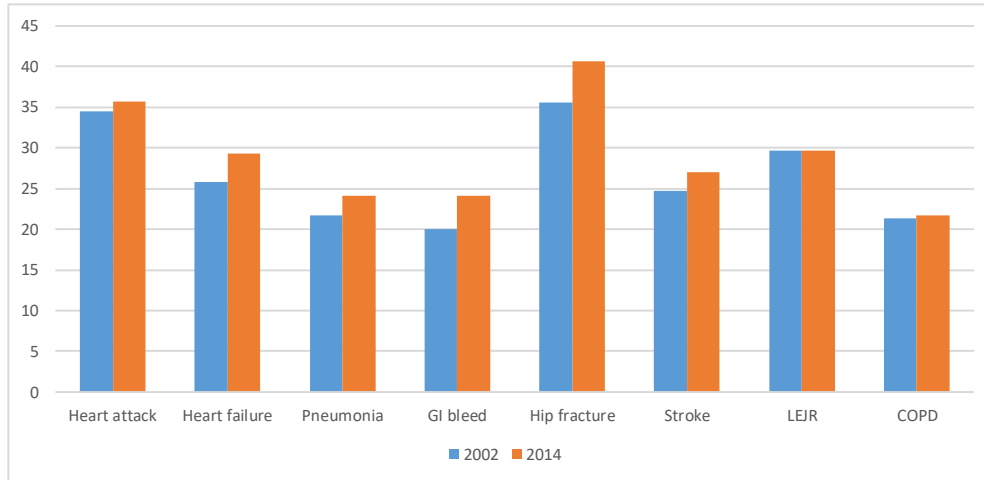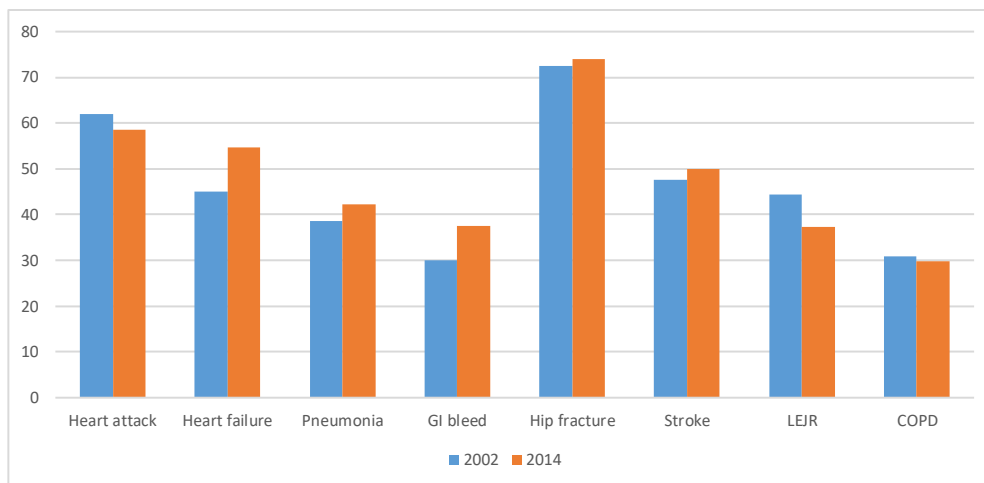
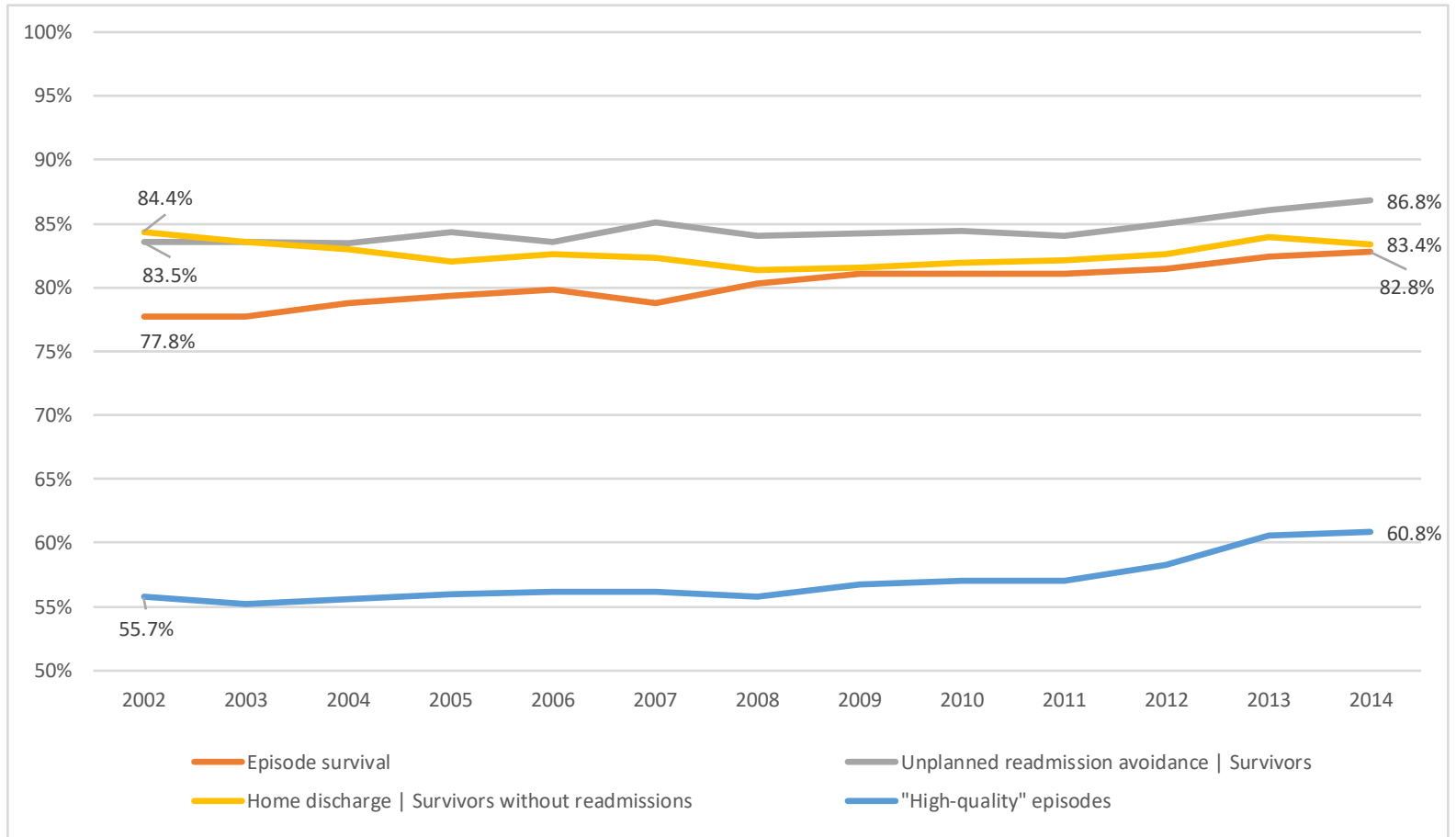Average Cost (000s of 2014 dollars)

Rate of "High-Quality" Episodes

Average Cost per "High-Quality" Episode (000s of 2014 Dollars)

Figure 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 4:
Select Patient Severity Measures for Heart-Attack Episodes
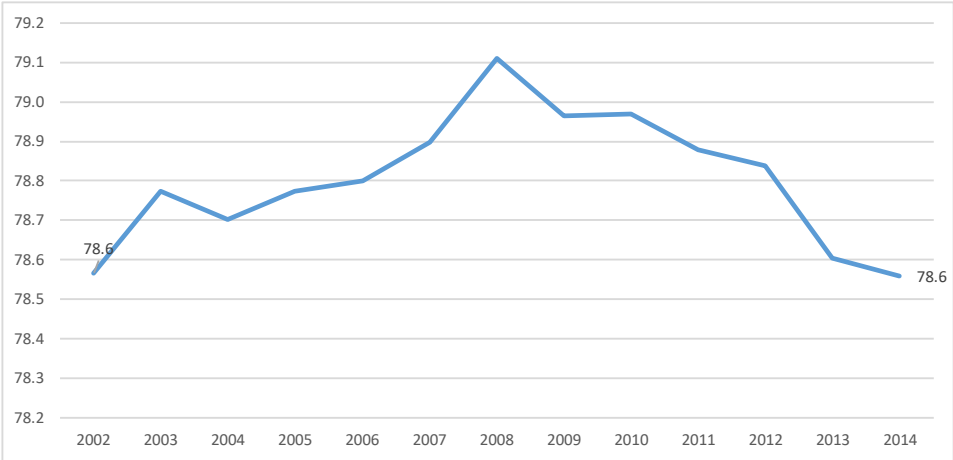
Average Age at Admission
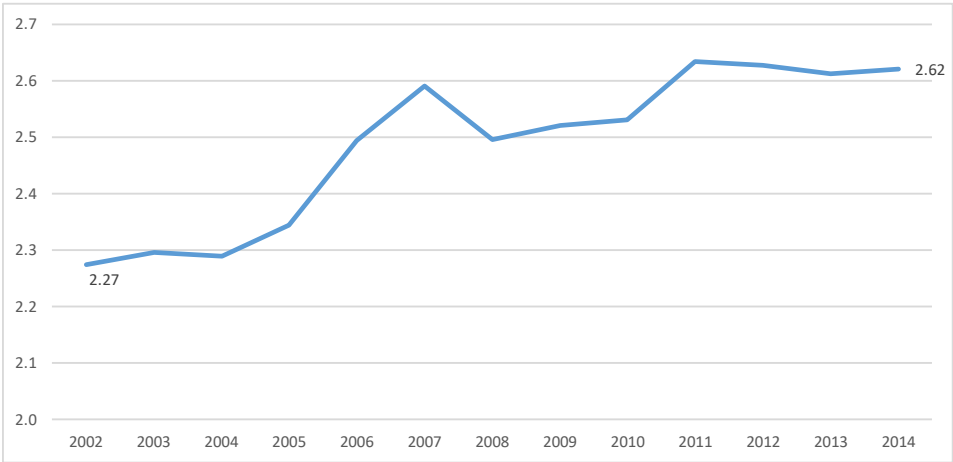
Number of Charlson-Deyo Comorbidities on Index Inpatient Record
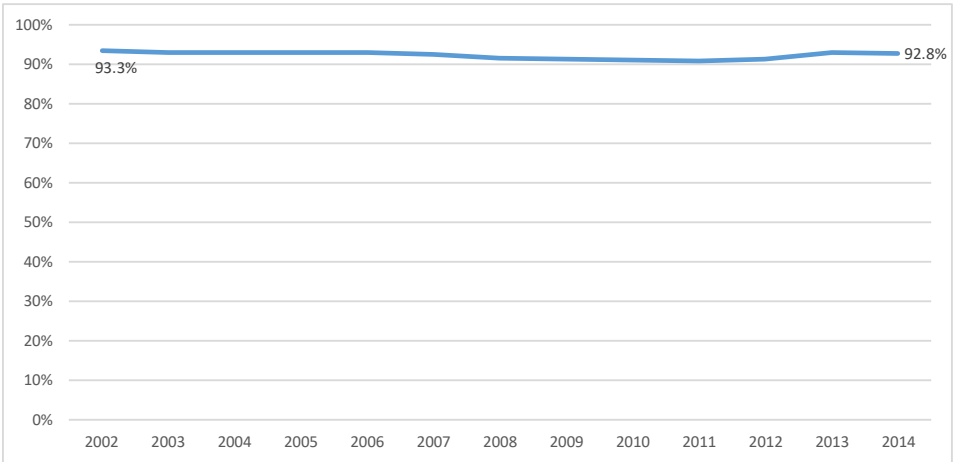
Predicted Inpatient Survival from AHRQ Inpatient Quality Indicator Risk Model

Figure 5:
Patient Severity Index among Heart-Attack Episodes
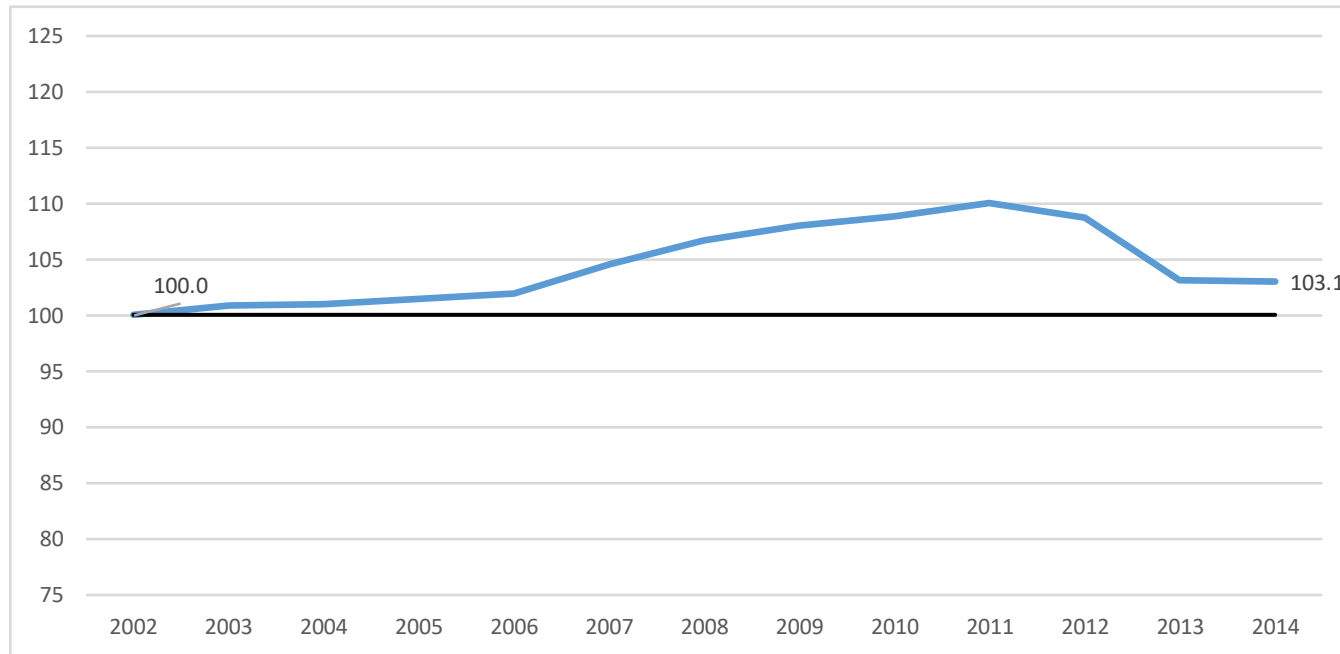
Note: We construct the patient severity index by exponentiating $-\overline{S}_{ht}\widehat{\beta}_S$, obtaining $\widehat{\beta}_S$ from the regression results corresponding to Figures 16 and 17 and normalizing the index to a value of 100 in 2002.

Figure 6:
Patient Severity Index among All Episodes
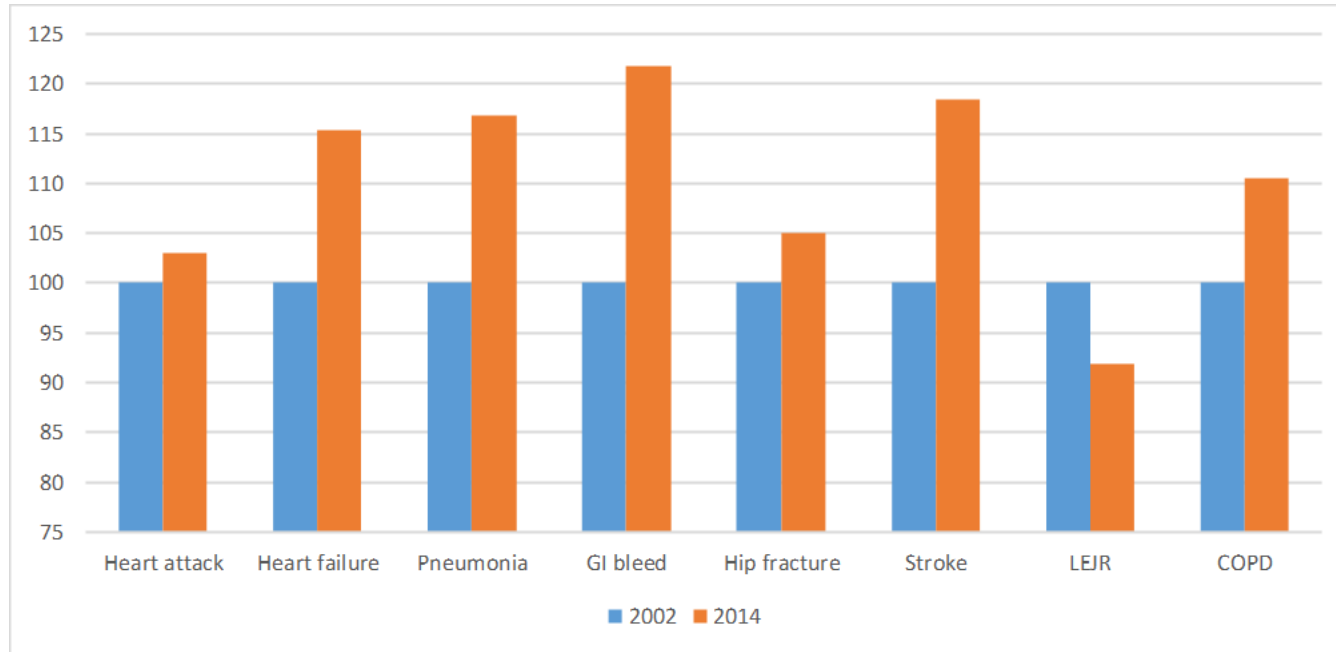
Note: We construct the patient severity index by exponentiating $-\overline{S}_{ht}\widehat{\beta}_S$, obtaining $\widehat{\beta}_S$ from the regression results corresponding to Figures 16 and 17 and normalizing the index to a value of 100 in 2002.

Figure 7:
Cumulative Change in Productivity Since 2002 in Treating Heart-Attack Episodes
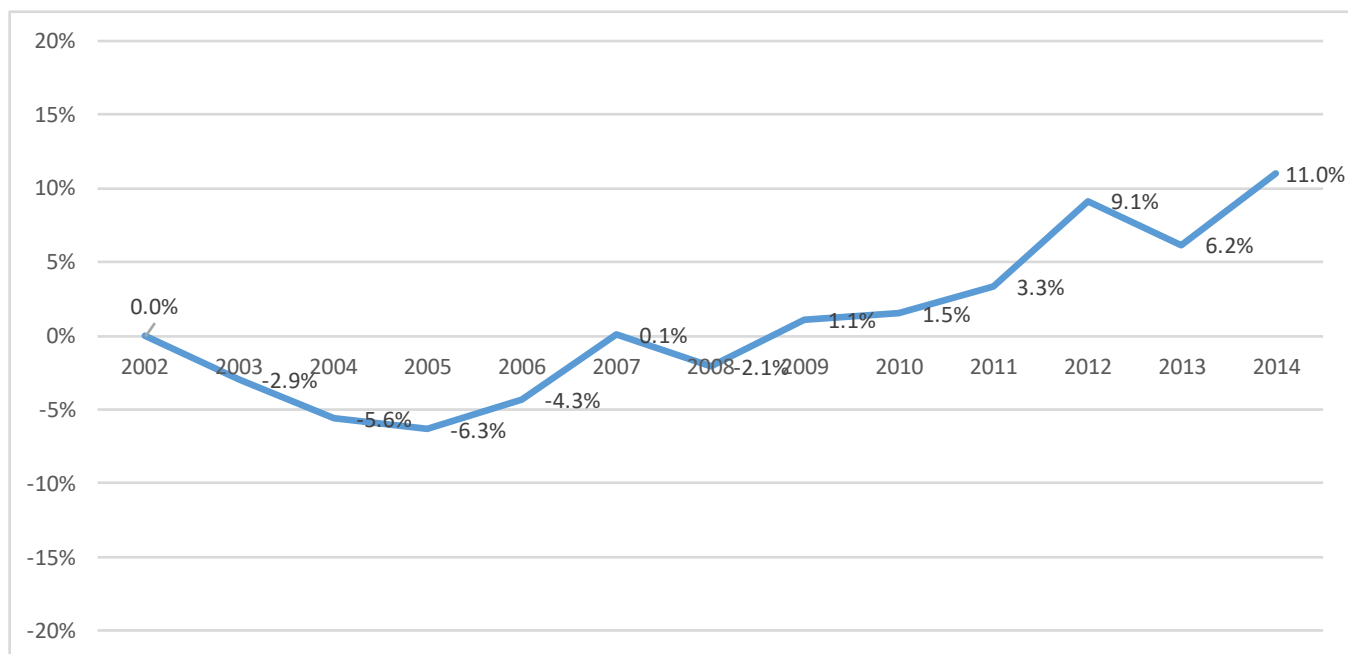
Figure 8:
Annualized Rate of Productivity Growth, 2002-2014
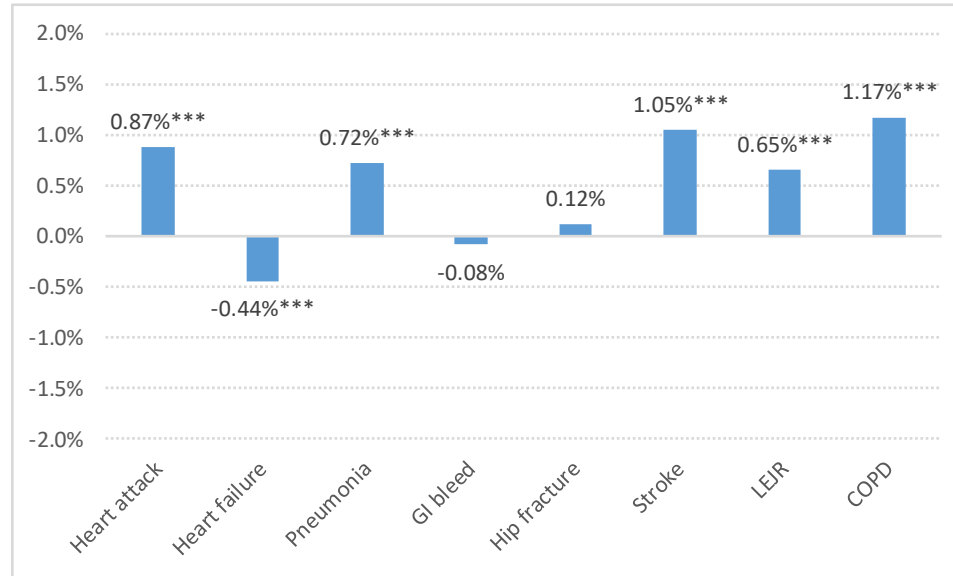
Notes: Rates calculated according to the formula $exp\left(\hat{b}_{2014}/12\right) - 1$, in which $\hat{b}_{2014}$ is the regression coefficient corresponding to episodes starting in 2014, relative to 2002. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 9:
Impacts of Adjustment for Outcome Quality and Patient Severity
on Annualized Productivity Growth Estimates
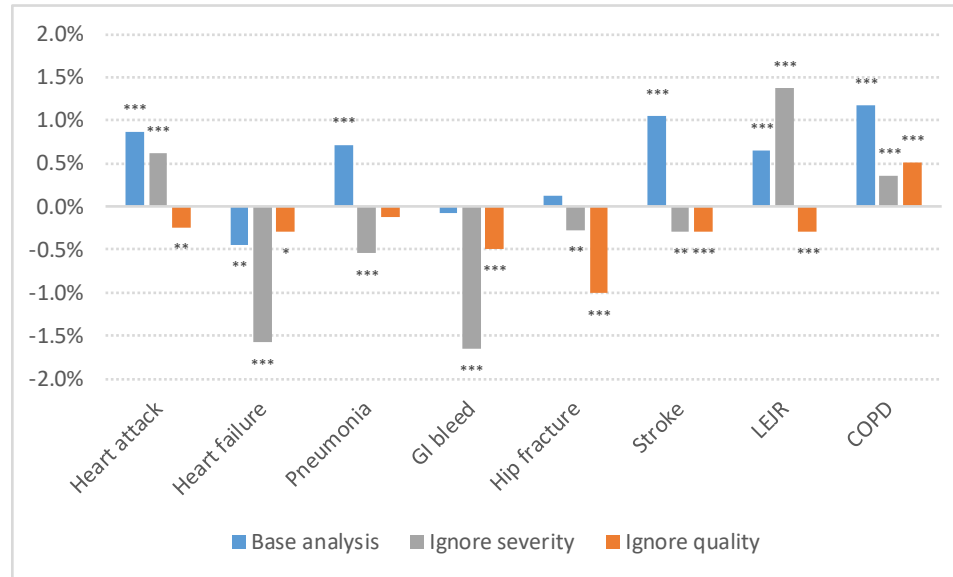
Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 10:
Sensitivity of Annualized Productivity Growth Estimates
to Quality of Life Decrement for Institutionalization
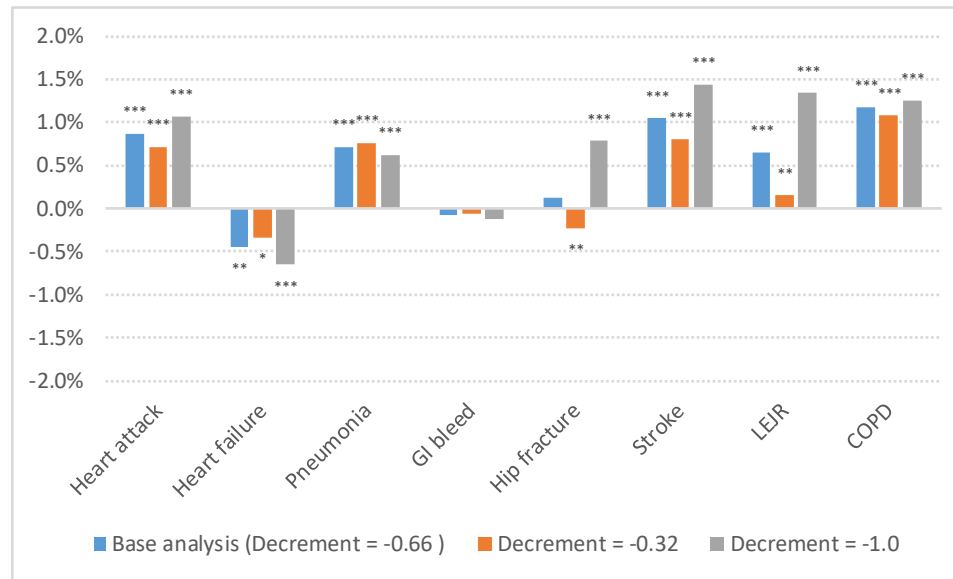
Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 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.

Figure 12:
Sensitivity of Annualized Productivity Growth Estimates
to Treatment of Missing Episode Costs

Notes: "Limited" missingness refers to episodes with a) 1 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 initia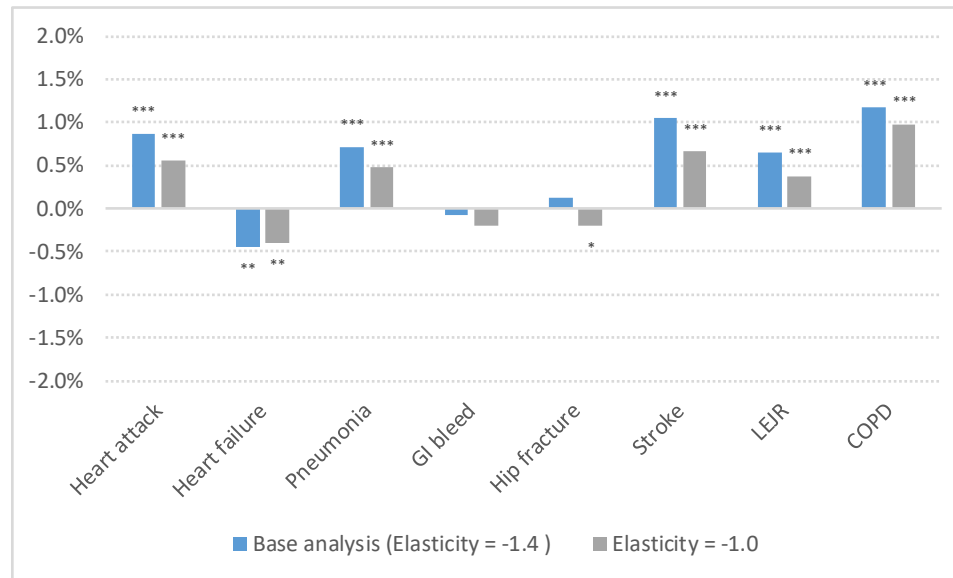ted in the same calendar year. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 13:
Sensitivity of Annualized Productivity Growth Estimates
to Inclusion of Hospital Fixed Effects

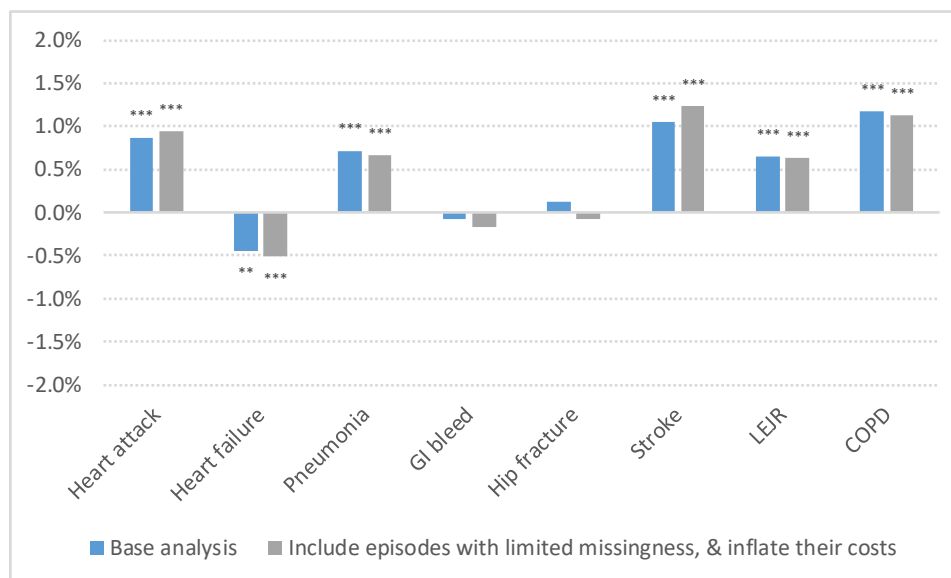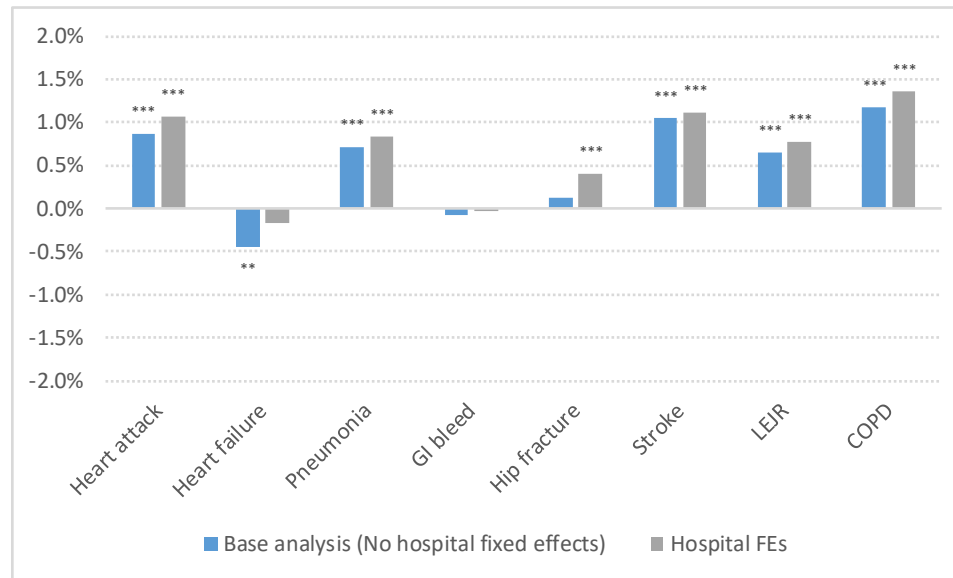

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 14:
Annualized Growth of Composite (All-Episode-Type) Productivity
According to Base Year
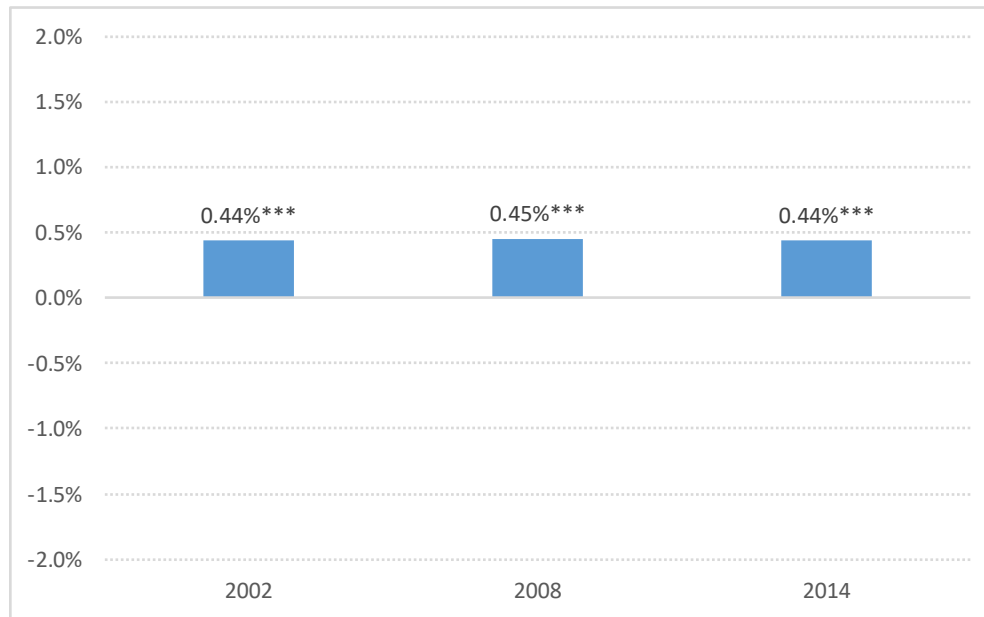
Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix Figure 1:
Overview of CMS Unplanned Readmission Algorithm

Appendix E.   Planned Readmission Algorithm

Figure PR.1 – Planned Readmission Algorithm Version 2.1 Flowchart
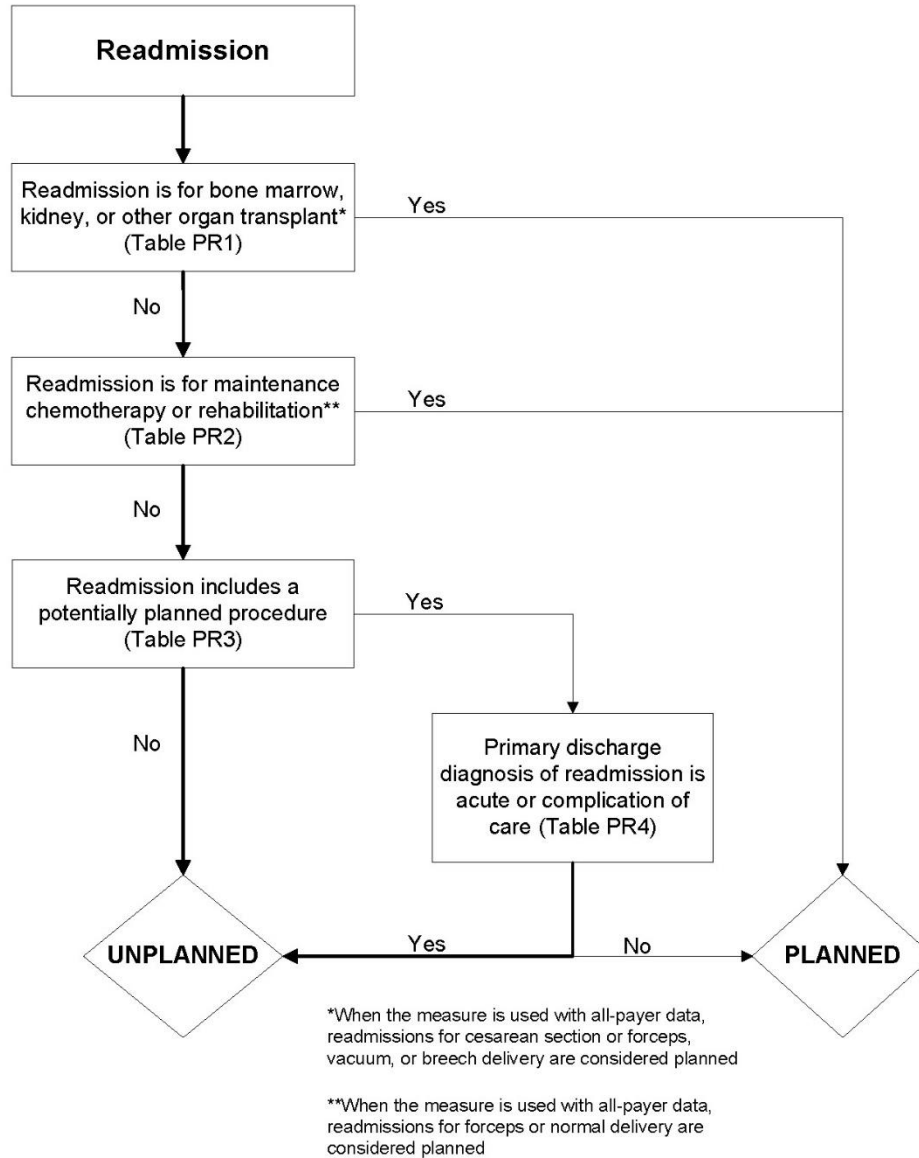
*When the measure is used with all-payer data, readmissions for cesarean section or forceps, vacuum, or breech delivery are considered planned

**When the measure is used with all-payer data, readmissions for forceps or normal delivery are considered planned

AHRQ

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.]

Appendix Figure 2, Continued

AHRQ QI™ ICD-9-CM Specification Version 6.0
IQI 15 Acute Myocardial Infarction Mortality Rate
www.qualityindicators.ahrq.gov

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

Appendix Figure 2, Continued

AHRQ QI™ ICD-9-CM Specification Version 6.0
IQI 15 Acute Myocardial Infarction Mortality Rate
www.qualityindicators.ahrq.gov

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

Appendix Figure 2, Continued

AHRQ QI™ ICD-9-CM Specification Version 6.0
IQI 15 Acute Myocardial Infarction Mortality Rate
www.qualityindicators.ahrq.gov

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)

AHRQ Quality Indicators™
Inpatient Quality Indicators (IQI) Parameter Estimates

Table 11. Risk Adjustment Coefficients for IQI 15 - Acute Myocardial Infarction (AMI) Mortality Rate

PARAMETER	LABEL	DF	ESTIMATE	STANDARD ERROR	WALD CHI-SQUARE	PR>CHI-SQUARE
Intercept	Intercept	1	-3.6765	0.4222	75.8134	<.0001
M_AgeCat_6	Male | Age < 55	1	-0.2537	0.0397	40.8156	<.0001
M_AgeCat_8	Male | Age < 65	1	0.0759	0.035	4.697	0.0302
M_AgeCat_9	Male | Age >= 65	1	0.0768	0.0328	5.4625	0.0194
M_AgeCat_11	Male | Age >= 75	1	0.1591	0.0282	31.798	<.0001
M_AgeCat_13	Male | Age >= 85	1	0.1453	0.0348	17.4855	<.0001
M_AgeCat_14	Male | Age >= 90	1	0.1218	0.0448	7.3979	0.0065
F_AgeCat_6	Female | Age < 55	1	-0.1659	0.0597	7.7307	0.0054
F_AgeCat_8	Female | Age < 65	1	-0.0325	0.0431	0.5659	0.4519
F_AgeCat_11	Female | Age >= 75	1	0.1075	0.0335	10.3035	0.0013
F_AgeCat_13	Female | Age >= 85	1	0.1112	0.0346	10.3116	0.0013
F_AgeCat_14	Female | Age >= 90	1	0.2911	0.0377	59.7157	<.0001
MDC_5	MDC 5: DISEASES & DISORDERS OF THE CIRCULATORY SYSTEM	1	2.1557	0.4199	26.3579	<.0001
ADX161_0001	DRG 161: Cardiac defibrillator & heart assist implant	1	-1.6775	0.5909	8.058	0.0045
ADX161_0002	DRG 161: Cardiac defibrillator & heart assist implant	1	-1.7192	0.2372	52.5474	<.0001
ADX161_0003	DRG 161: Cardiac defibrillator & heart assist implant	1	-1.512	0.129	137.3374	<.0001
ADX161_0004	DRG 161: Cardiac defibrillator & heart assist implant	1	0.5553	0.0607	83.5733	<.0001
ADX162_0003	DRG 162: Cardiac valve procedures w cardiac catheterization	1	-1.9697	0.2068	90.7299	<.0001
ADX162_0012	DRG 162: Cardiac valve procedures w cardiac catheterization	1	-3.5914	0.5804	38.2825	<.0001

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Appendix Figure 3, Continued

| PARAMETER	LABEL	DF	ESTIMATE	STANDARD ERROR	WALD CHI-SQUARE	PR>CHI-SQUARE
ADX163_0003	DRG 163: Cardiac valve procedures w/o cardiac catheterization	1	-2.286	0.4544	25.3048	<.0001
ADX163_0012	DRG 163: Cardiac valve procedures w/o cardiac catheterization	1	-2.357	0.5852	16.2216	<.0001
ADX165_0003	DRG 165: Coronary bypass w cardiac cath or percutaneous cardiac procedure	1	-2.7485	0.0899	934.1475	<.0001
ADX165_0004	DRG 165: Coronary bypass w cardiac cath or percutaneous cardiac procedure	1	-0.7461	0.0585	162.5885	<.0001
ADX165_0012	DRG 165: Coronary bypass w cardiac cath or percutaneous cardiac procedure	1	-4.5302	0.1782	646.075	<.0001
ADX166_0003	DRG 166: Coronary bypass w/o cardiac cath or percutaneous cardiac procedure	1	-2.9037	0.1974	216.3155	<.0001
ADX166_0004	DRG 166: Coronary bypass w/o cardiac cath or percutaneous cardiac procedure	1	-0.5389	0.1036	27.0435	<.0001
ADX166_0012	DRG 166: Coronary bypass w/o cardiac cath or percutaneous cardiac procedure	1	-5.2789	0.5018	110.6855	<.0001
ADX167_0004	DRG 167: Other cardiothoracic procedures	1	0.8715	0.296	8.6713	0.0032
ADX167_0123	DRG 167: Other cardiothoracic procedures	1	-0.9615	0.4683	4.2156	0.0401
ADX169_0002	DRG 169: Major thoracic & abdominal vascular procedures	1	-2.3345	1.0119	5.322	0.0211
ADX169_0003	DRG 169: Major thoracic & abdominal vascular procedures	1	-1.6476	0.5915	7.7588	0.0053
ADX169_0004	DRG 169: Major thoracic & abdominal vascular procedures	1	0.8006	0.226	12.5455	0.0004
ADX170_0003	DRG 170: Permanent cardiac pacemaker implant w AMI heart failure or shock	1	-2.4126	0.2732	77.9654	<.0001
ADX173_0003	DRG 173: Other vascular procedures	1	-1.599	0.2082	58.9771	<.0001
ADX173_0004	DRG 173: Other vascular procedures	1	0.6323	0.1469	18.5311	<.0001
ADX173_0012	DRG 173: Other vascular procedures	1	-1.7646	0.5897	8.9546	0.0028
ADX174_0001	DRG 174: Percutaneous cardiovascular procedures w AMI	1	-5.4385	0.1131	2313.699	<.0001

Appendix Figure 3, Continued

AHRQ Quality Indicators™
Inpatient Quality Indicators (IQI) Parameter Estimates

PARAMETER	LABEL	DF	ESTIMATE	STANDARD ERROR	WALD CHI-SQUARE	PR>CHI-SQUARE
ADX174_0002	DRG 174: Percutaneous cardiovascular procedures w AMI	1	-4.1135	0.0717	3291.108	<.0001
ADX174_0003	DRG 174: Percutaneous cardiovascular procedures w AMI	1	-2.288	0.0532	1847.254	<.0001
ADX174_0004	DRG 174: Percutaneous cardiovascular procedures w AMI	1	0.2224	0.0405	30.1245	<.0001
ADX175_0001	DRG 175: Percutaneous cardiovascular procedures w/o AMI	1	-4.6469	1.0018	21.5166	<.0001
ADX175_0002	DRG 175: Percutaneous cardiovascular procedures w/o AMI	1	-2.7821	0.5828	22.7908	<.0001
ADX175_0003	DRG 175: Percutaneous cardiovascular procedures w/o AMI	1	-1.3744	0.3915	12.3253	0.0004
ADX176_0034	DRG 176: Cardiac pacemaker & defibrillator device replacement	1	-1.727	0.7246	5.6799	0.0172
ADX180_0003	DRG 180: Other circulatory system procedures	1	-1.2703	0.3138	16.3888	<.0001
ADX180_0012	DRG 180: Other circulatory system procedures	1	-2.3913	0.7158	11.1597	0.0008
ADX190_0001	DRG 190: Acute myocardial infarction	1	-4.2908	0.1255	1168.52	<.0001
ADX190_0002	DRG 190: Acute myocardial infarction	1	-2.8623	0.0588	2367.434	<.0001
ADX190_0003	DRG 190: Acute myocardial infarction	1	-1.3875	0.0403	1185.963	<.0001
ADX190_0004	DRG 190: Acute myocardial infarction	1	0.7259	0.0393	340.8797	<.0001
ADX191_0001	DRG 191: Cardiac catheterization w circ disord exc ischemic heart disease	1	-3.1417	1.0053	9.7658	0.0018
ADX191_0002	DRG 191: Cardiac catheterization w circ disord exc ischemic heart disease	1	-3.2554	1.0052	10.4873	0.0012
ADX198_0001	DRG 198: Angina pectoris & coronary atherosclerosis	1	-1.2529	0.3681	11.5852	0.0007
ADX198_0002	DRG 198: Angina pectoris & coronary atherosclerosis	1	-1.0658	0.2262	22.1947	<.0001
ADX198_0003	DRG 198: Angina pectoris & coronary atherosclerosis	1	-0.4057	0.1769	5.2596	0.0218
TRNSFER	Transfer Status	1	0.0294	0.0211	1.9368	0.164

c-statistic=0.894

Appendix Figure 4:
Other Hospital Production Index among Heart-Attack Episodes
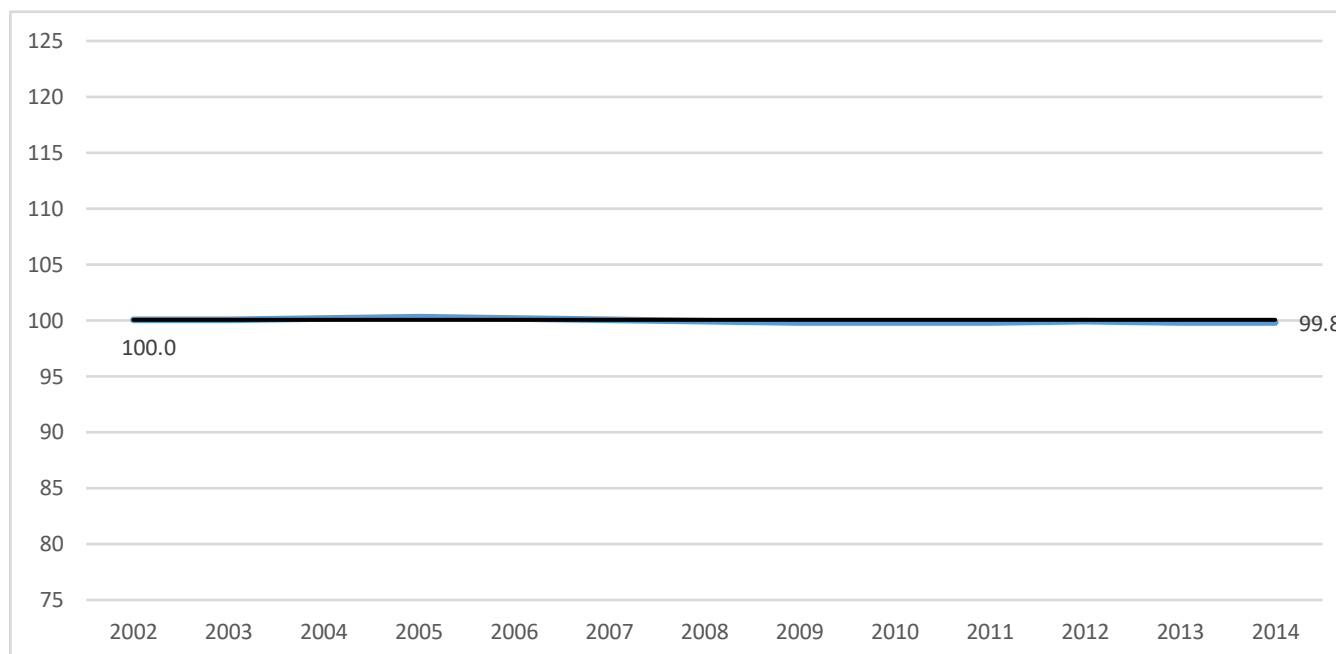
Note: We construct the patient severity index by exponentiating $-\overline{\boldsymbol{O}}_{ht}\widehat{\boldsymbol{\beta}}_{\boldsymbol{O}}$, obtaining $\widehat{\boldsymbol{\beta}}_{\boldsymbol{O}}$ from the regression results corresponding to Figures 16 and 17 and normalizing the index to a value of 100 in 2002.

Appendix Figure 5:
Cumulative Change in Productivity Since 2002
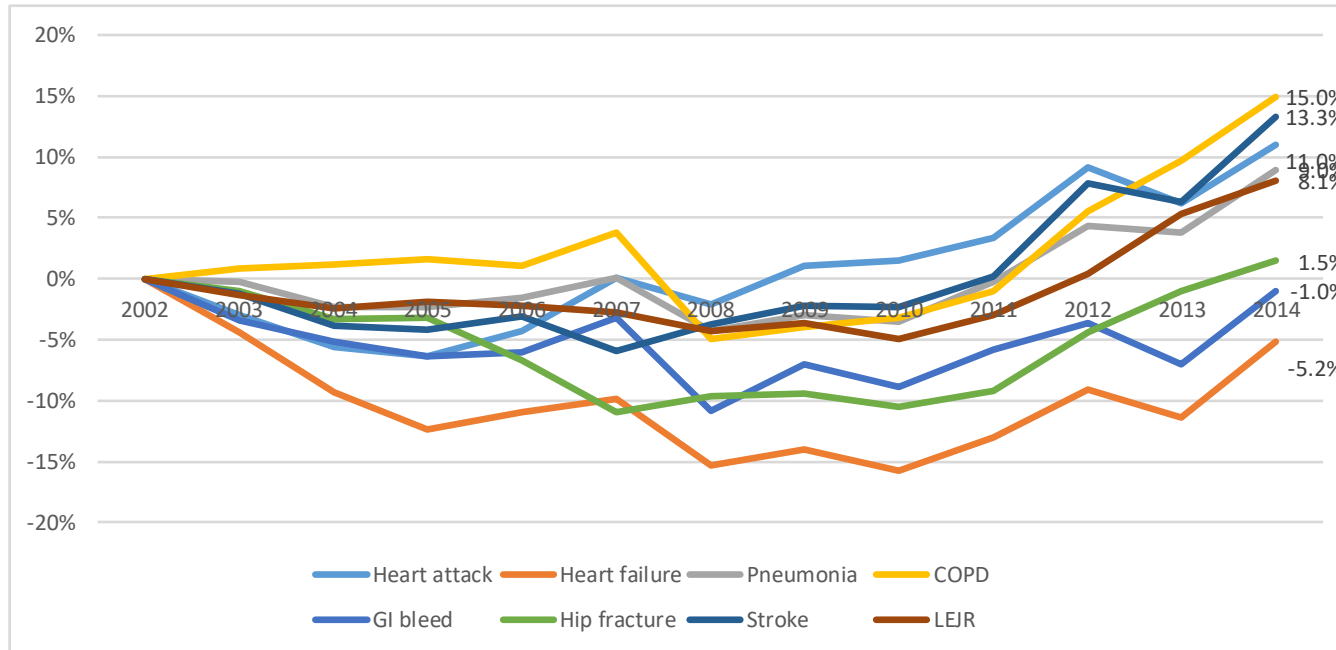
Complete Results from Baseline Regressions

Episode type	Heart attack	Heart failure	Pneumonia	GI bleed	Hip fracture	Stroke	LEJR	COPD
Coefficient (Standard Error)								
Constant	-8.618*** (0.628)	-1.571** (0.701)	5.581*** (0.653)	2.195*** (0.600)	4.473*** (0.565)	5.085*** (0.585)	2.131*** (0.703)	0.337 (0.599)
2003 episode	-0.030*** (0.011)	-0.045*** (0.010)	-0.003 (0.010)	-0.035*** (0.013)	-0.010 (0.012)	-0.012 (0.015)	-0.014* (0.008)	0.008 (0.012)
2004 episode	-0.058*** (0.012)	-0.098** (0.010)	-0.023* (0.010)	-0.053*** (0.012)	-0.033*** (0.012)	-0.039*** (0.015)	-0.024*** (0.008)	0.011 (0.012)
2005 episode	-0.065*** (0.012)	-0.132*** (0.011)	-0.023** (0.010)	-0.065*** (0.013)	-0.032*** (0.012)	-0.043*** (0.015)	-0.019** (0.008)	0.015 (0.012)
2006 episode	-0.044*** (0.013)	-0.116*** (0.011)	-0.015 (0.010)	-0.063*** (0.013)	-0.069*** (0.012)	-0.032** (0.015)	-0.022*** (0.008)	0.011 (0.012)
2007 episode	0.001 (0.013)	-0.104*** (0.013)	0.001 (0.011)	-0.033** (0.014)	-0.116*** (0.014)	-0.061*** (0.015)	-0.028*** (0.009)	0.038*** (0.013)
2008 episode	-0.021 (0.013)	-0.166*** (0.015)	-0.044*** (0.012)	-0.115*** (0.014)	-0.102*** (0.012)	-0.038** (0.015)	-0.044*** (0.009)	-0.051*** (0.013)
2009 episode	0.011 (0.013)	-0.151*** (0.017)	-0.030** (0.012)	-0.072*** (0.014)	-0.099*** (0.012)	-0.023 (0.016)	-0.036*** (0.009)	-0.040*** (0.013)
2010 episode	0.015 (0.013)	-0.172*** (0.018)	-0.036*** (0.012)	-0.093*** (0.014)	-0.111*** (0.013)	-0.023 (0.015)	-0.050*** (0.009)	-0.033** (0.013)
2011 episode	0.033** (0.014)	-0.139*** (0.019)	-0.002 (0.012)	-0.060*** (0.015)	-0.096*** (0.012)	0.002 (0.015)	-0.030*** (0.009)	-0.010 (0.013)
2012 episode	0.088*** (0.014)	-0.095*** (0.020)	0.042*** (0.013)	-0.037** (0.015)	-0.045*** (0.013)	0.075*** (0.015)	0.004 (0.009)	0.054*** (0.013)
2013 episode	0.060*** (0.014)	-0.121*** (0.020)	0.038*** (0.013)	-0.073*** (0.014)	-0.010 (0.013)	0.062*** (0.015)	0.051*** (0.009)	0.092*** (0.013)
2014 episode	0.104*** (0.017)	-0.053** (0.023)	0.086*** (0.015)	-0.010 (0.017)	0.014 (0.015)	0.125*** (0.018)	0.078*** (0.011)	0.139*** (0.015)
AHRQ predicted inpatient survival, logged	3.043*** (0.089)	8.184*** (0.317)	6.968*** (0.175)	7.215*** (0.185)	3.266*** (0.141)	4.141*** (0.123)	—	—
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)	—	—	—	—	—	—	—	—
No Charlson-Deyo comorbidities	—	—	—	—	—	—	—	—
1 Charlson-Deyo comorbidity	0.369*** (0.041)	0.101 (0.179)	-0.126*** (0.031)	-0.167*** (0.026)	-0.171*** (0.018)	0.788*** (0.036)	-0.122*** (0.018)	0.696*** (0.051)
2 Charlson-Deyo comorbidities	0.198** (0.039)	-0.338*** (0.031)	-0.338*** (0.031)	-0.464*** (0.029)	-0.283*** (0.023)	0.621*** (0.037)	-0.294*** (0.029)	0.437*** (0.052)
3 Charlson-Deyo comorbidities	0.086** (0.042)	-0.129 (0.182)	-0.524*** (0.040)	-0.601*** (0.037)	-0.389*** (0.033)	0.318*** (0.037)	-0.406*** (0.047)	0.289*** (0.055)
4 Charlson-Deyo comorbidities	0.027 (0.047)	-0.245 (0.184)	-0.578*** (0.055)	-0.722*** (0.046)	-0.454*** (0.054)	0.159*** (0.040)	-0.545*** (0.075)	0.180*** (0.062)
5+ Charlson-Deyo comorbidities	—	-0.325* (0.185)	-1.032*** (0.062)	-1.059*** (0.051)	-0.418*** (0.061)	—	—	—
Age, logged	0.734*** (0.105)	-0.356*** (0.123)	-2.007*** (0.110)	-1.208*** (0.102)	-1.819*** (0.084)	-1.970*** (0.101)	-1.667*** (0.103)	-0.909*** (0.108)
Female	0.037* (0.022)	-0.038 (0.024)	-0.092*** (0.022)	-0.043** (0.021)	0.043*** (0.018)	-0.133*** (0.020)	-0.062*** (0.018)	-0.115*** (0.020)
White	0.176*** (0.061)	0.258*** (0.063)	0.140** (0.059)	0.121** (0.048)	0.116** (0.047)	0.278*** (0.056)	0.199*** (0.054)	0.225*** (0.055)
African American	0.146** (0.068)	0.243*** (0.066)	-0.117* (0.068)	-0.088 (0.055)	-0.079 (0.060)	0.072 (0.062)	-0.006 (0.068)	0.086 (0.062)
Hispanic	0.678*** (0.105)	0.771*** (0.114)	0.516*** (0.114)	0.399*** (0.093)	0.531*** (0.084)	0.823*** (0.110)	0.508*** (0.126)	0.613*** (0.102)
Other race	—	—	—	—	—	—	—	—
1st quarter of year episode	—	—	—	—	—	—	—	—
2nd quarter of year episode	0.033 (0.028)	-0.013 (0.031)	0.006 (0.028)	0.034 (0.026)	0.015 (0.022)	0.013 (0.027)	-0.020 (0.021)	-0.029 (0.024)
3rd quarter of year episode	0.014 (0.030)	-0.074** (0.031)	-0.137*** (0.030)	-0.022 (0.026)	-0.001 (0.020)	0.025 (0.027)	-0.053** (0.020)	-0.098*** (0.028)
4th quarter of year episode	-0.009 (0.030)	-0.006 (0.032)	-0.021 (0.030)	-0.036 (0.026)	-0.018 (0.022)	0.006 (0.028)	-0.048** (0.022)	-0.006 (0.026)
Patient zip code characteristics								
Median household income ($000)	-0.006*** (0.001)	-0.010*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.007*** (0.001)	-0.010*** (0.001)
Social Security income ($000)	-0.006 (0.009)	-0.018* (0.010)	-0.019** (0.009)	-0.022*** (0.008)	-0.014 (0.009)	0.004 (0.009)	-0.022** (0.009)	
Poor	0.569** (0.252)	-0.459* (0.242)	0.293 (0.226)	0.239 (0.226)	0.552*** (0.180)	0.072 (0.248)	0.639*** (0.227)	-0.109 (0.216)
Employed	2.105*** (0.397)	0.573* (0.345)	1.179*** (0.371)	1.228*** (0.336)	-0.125 (0.287)	0.207 (0.353)	0.472 (0.363)	1.062*** (0.340)
Less than high school education	-0.004 (0.155)	-0.188 (0.143)	-0.604*** (0.130)	-0.453*** (0.126)	-0.424*** (0.113)	-0.322** (0.144)	-0.571*** (0.130)	-0.186 (0.139)
Urban	-0.086** (0.036)	-0.123*** (0.035)	-0.138*** (0.030)	-0.141*** (0.032)	-0.150*** (0.026)	-0.155*** (0.035)	-0.050 (0.034)	-0.115*** (0.031)
Hispanic	-0.581*** (0.062)	-0.593*** (0.065)	-0.574*** (0.059)	-0.517*** (0.057)	-0.552*** (0.048)	-0.654*** (0.062)	-0.482*** (0.065)	-0.677*** (0.066)
Single	-0.757*** (0.158)	-0.702*** (0.154)	-0.530*** (0.149)	-0.483*** (0.151)	-0.732*** (0.150)	-0.698*** (0.154)	-0.804*** (0.151)	-0.695*** (0.156)
Elderly in an institution	-0.034 (0.200)	0.547*** (0.209)	-0.173 (0.189)	0.206 (0.166)	-0.172 (0.133)	0.093 (0.164)	0.375** (0.171)	0.203 (0.172)
Non-institutionalized elderly with physical disability	0.385* (0.221)	0.236 (0.239)	-0.137 (0.219)	-0.077 (0.200)	-0.134 (0.163)	-0.015 (0.213)	-0.236 (0.192)	0.282 (0.221)
Mental disability	-0.494 (0.338)	-0.731** (0.325)	-0.345 (0.308)	-0.049 (0.279)	-0.325 (0.235)	0.013 (0.317)	0.046 (0.265)	-0.781*** (0.296)
Sensory disability among elderly	0.056 (0.296)	-0.008 (0.332)	0.537* (0.296)	-0.095 (0.276)	0.204 (0.200)	-0.070 (0.264)	0.045 (0.233)	0.152 (0.288)
Self-care disability	-0.214 (0.393)	0.445 (0.364)	0.375 (0.369)	0.020 (0.360)	0.319 (0.271)	-0.510 (0.368)	0.157 (0.312)	-0.130 (0.340)
Difficulty going-outside-the-home disability	-0.124 (0.271)	-0.353 (0.269)	-0.760*** (0.257)	-0.267 (0.253)	-0.268 (0.191)	0.001 (0.251)	0.124 (0.234)	-0.352 (0.258)
Index hospital characteristics								
Residents per bed = 0	—	—	—	—	—	—	—	—
Residents per bed > 0 and ≤ 0.25	-0.077*** (0.011)	-0.071*** (0.011)	-0.009 (0.010)	-0.049*** (0.010)	-0.021** (0.009)	-0.068*** (0.011)	0.017* (0.010)	-0.047*** (0.011)
Residents per bed > 0.25 and ≤ 0.6	-0.158*** (0.020)	-0.173*** (0.022)	-0.087*** (0.021)	-0.167*** (0.021)	-0.057*** (0.018)	-0.154*** (0.022)	0.003 (0.019)	-0.124*** (0.022)
Residents per bed > 0.6	-0.181*** (0.027)	-0.211*** (0.027)	-0.055* (0.033)	-0.188*** (0.035)	-0.055* (0.030)	-0.211*** (0.027)	-0.041 (0.026)	-0.092*** (0.033)
Other Statistics								
Hospital-years, n	28,635	39,650	40,735	36,804	29,800	32,006	34,073	39,478
R squared	0.191	0.227	0.268	0.243	0.170	0.248	0.326	0.166