Measuring the Quality of English NHS Acute Trusts

Irene Papanicolas[1], Alistair McGuire[1], Maria Raikou[1], Elias Mossialos[1], Simon Jones[2]

Contact: i.n.papanicolas@lse.ac.uk
[1] LSE Health, The London School of Economics, London
[2] Kings College, London

Abstract

"The ultimate goal is to manage quality. But you cannot manage it until you have a way to measure it, and you cannot measure it until you can monitor it." (Florence Nightingale)

The provision of performance information is essential for ensuring and improving the performance of health care systems. However, the lack of reliable quality information is a key problem in evaluating and improving health care. This paper estimates the performance of English NHS Acute Trusts using Dr. Foster data from the years 1996-2008 to investigate health outcomes after elective treatment for acute myocardial infarction (AMI), stroke, TIA, heart disease and hip replacement. Short-term mortality and readmission rates adjusted for patient characteristics are calculated for each year and then used to compare current and past quality of care across NHS Acute Trusts. Our results support that this method is better suited to measuring quality of care and better able to predict future patient outcomes than existing indicators. Using these quality measures we are able to investigate the performance of NHS Acute Trusts across this time period and identify hospitals where further scrutiny of low quality is required in the future.

THIS PAPER IS A WORK IN PROGRESS: DO NOT QUOTE WITHOUT THE AUTHOR'S PERMISSION

1 Introduction

Health system performance is currently high on national and international policy agendas. The past decades have seen a large development in the scope and use of performance measurement, which serves as an essential component of health system improvement. Information is crucial for the delivery of effective, equitable and efficient health care services, as well as for managerial purposes, such as ensuring accountability and transparency. Most industrialized countries collect a variety of performance measures, both on the macro and micro levels, to adequately capture the different aspects and objectives that are important. Indicators range from population health measures and health status to non-medical determinants of health, health system performance and patient accounts of experiences and satisfaction with their health system encounters. While this information is essential to health policy, there are several methodological challenges in developing and interpreting indicators that need to be recognized.

A key area in performance measurement of health systems is that of quality of care of health care providers. Being able to measure quality of care is desirable, as it can assist patients in selecting the most appropriate provider for care, and also to inform policy through the assessment of reforms that have been and are being implemented in order to achieve wider health system goals such as efficiency or equity. However, despite the demand for such information, little reliable quality of care information is available. There are several reasons which contribute to this lack of available quality information (McClellan and Staiger, 1999). The first major hurdle is that often timely and relevant data on patient outcomes does not exist because it is costly and difficult to collect. Yet, even when such data is available it is not easy to use. This is because outcome data usually reflects a wide range of dimensions that influence patient outcomes, only one of which is quality of care. Moreover, sometimes these factors may systematically be correlated with the patient mix of certain providers and thus result in biased measures, for example if a hospital is located in a deprived area it will treat more deprived patients and is likely to have worse outcomes irrespective of the quality it provides. Thus, using pure outcome measures to hold providers to account without adequately adjusting for the other factors that can influence quality would run the risk of being counterproductive. Even quality of care itself has many dimensions, outcomes being only one of these. Clinical processes of care are also an important dimension as is safety of care and responsiveness (Legido_Quigley et al., 2008). An ideal quality indicator would take all these relevant dimensions into account.

In this paper, a framework for using existing data in England is suggested to address some of these main issues in the provision of quality information. Measures of two major health outcome indicators for patients are developed to measure the performance of NHS Acute hospital trusts over time.

2 Background

Indicators of health system performance can be used for numerous purposes, such as: to secure accountability in the system, to determine appropriate treatment for patients, to facilitate patient choice, to compare across jurisdictions, programs and systems, and to inform management and policy decisions. In recent decades there have been increasing large-scale efforts to measure health system performance, driven in part by the effort to contain costs and improve accountability and facilitated by improved systems of data collection (Power, 1999; Smith, 2005).

Outcome, Process & Structural measures

Quality and effectiveness of care are important dimensions of performance; they are measured with structure, process and outcome indicators (Donabedian, 1966). Structure indicators measure the technical and static elements of healthcare systems such as number of beds, or qualifications of health care professionals. Outcome indicators measure the impact that health interventions have on patient outcomes, while process indicators measure what is done for and to patients (Naylor, Iron, & Handa, 2002).

Outcome indicators are desirable because they measure the actual impact of health care on health; however, health outcomes are affected not only by health care, but also patient characteristics, such as age, education or income (Mant, 2001). To some extent these differences can be controlled for through proper risk adjustment, though it may not be possible to control for all relevant patient characteristics (Iezzoni, forthcoming). Other difficulties arise in collecting outcome indicators, for example, the long time lag between a health intervention and health outcome. Outcome indicators are therefore advocated only in specific circumstances, such as for homogenous diagnoses with strong causal pathways between interventions and outcomes, and for heterogeneous populations where outcomes can be linked back to a common cause (e.g. rates of post-operative infection) (Naylor et al., 2002).

Process indicators are arguably more sensitive measures of quality of care and easier to interpret than outcome indicators. For the specific example of treatment of myocardial infarction, the proportion of patients with hypertension who are taking hypertensive medicines is a process measure that directly measures quality of care, whereas measuring rates of mortality following myocardial infarction is an indirect measure of quality. Moreover there may be differences in the outcome measure which are not attributable to quality of care (Mant, 2001), for example lifestyle factors in the case of myocardial infarction.

Methodological approaches to solve this (McClellan and Staiger, 1999) & Bayesian techniques

Using aggregate variables, such as average death rates, in combination with individual observations by trust or site to determine relationships through regressions or other statistical models runs the risk of producing downwards biased standard errors, and possibly exaggerating the significance of certain effects based on spurious associations (Moulton, 1990).

3 Empirical Model

This paper analyses the determinants of hospital trust quality through a two-step process, with hospital trusts being the unit of analysis. In the first step, individual patient level data is used to create filtered outcome measures at the hospital trust level using multiple individual outcome measures (such as mortality and readmission rates), adjusted for individual level patient characterises. This filtering process allows the amount of noise surrounding these outcome measures to be minimized, thus creating more robust quality measures at the hospital trust level. These filtered outcome measures are then used in the second step to examine how different hospital and social characteristics influence quality of care.

Creating Filtered Outcome Measures

The first step of the analysis uses the quality measures provided at the individual patient level over a given amount of years to estimate the relative difference in the mean value of outcomes of each hospital holding patient characteristics constant. These hospital intercepts are estimated using the following equation:

$$Y_{ijt}^{k} = b_{1}^{k} X_{1jt}^{k} + b_{2}^{k} X_{2ijt}^{k} + u_{itj} \qquad (1)$$

where Y^k represents the quality outcome measure (30 day mortality and 28 day readmission), with i denoting the individual patient, j the hospital and t the year. X_2 controls for various patient characteristics (age, gender, socioeconomic deprivation, co-morbidities and whether surgery was elective or emergency). X_1 denotes a group of control variables representing all hospital trusts in which treatment was provided to the sample of patients. Thus $b^k{}_1$ measures the difference in the quality outcome measure k, in year t, associated with the hospital trust in which the treatment was undertaken and controlling for patient characteristics.

This patient level regression is run separately for each year t and quality outcome measure k. By saving the $b^k{}_1$ coefficients for each regression, we are able to estimate a vector of hospital intercepts for each quality outcome measure k, and year t. These estimates of quality are appealing as they provide relative rankings of hospital performance contributing to the quality outcomes, controlling for other external influences. These estimates thus allow some of the noise in estimates to be removed from the outcome measures, and thus enable a more appropriate comparison of hospital trusts to one another.

Panel Data Estimation with Lagged Variables

Just as the performance of hospitals in obtaining a desired outcome for their patients will be influenced by the characteristics of patients, it will also depend on other factors such as the characteristics of the hospital itself. The literature has shown, that different types of hospitals (teaching, acute, specialist) may be associated with different quality care (ref). Similarly, factors such as the size of the hospital (how many patients treated), and relative average deprivation of the patients admitted may also contribute to overall performance (ref). Moreover, to some extent a hospital trust's performance in one year is likely to depend on its performance in the past years. The second step of this analysis uses these hospital intercepts to estimate the influence of some of these factors on relative hospital performance in achieving the selected outcome measures.

Using the hospital intercepts from regression in step one for each year, and each quality measure, allows the creation of a new panel data set at the hospital level containing information for each of the years. This data set contains the newly created filtered quality outcome measure for each year, along with the existing hospital characteristics information that was available in the individual data. In addition, it is possible to estimate a set of variables for each year in the data corresponding to the average socioeconomic and demographic characteristics of the patients treated by each hospital.

In order to examine how these factors influence the performance of hospitals on the quality outcome measures the following equation is estimated using the new panel dataset created:

$$Q_{jt} = a + b_1 Q_{j(t-n)} + b_1 X_{1jt} + b_2 X_{2jt} + b_3 X_t + u_{jt} \quad (2)$$

Where Q_{jt} represents the hospital intercept estimated in the first step, and represents the filtered outcome measures for each hospital j at year t. The lag variable $Q_{j(t-n)}$ takes into account the filtered outcome measure of n years prior to year t, while variables X_1 and X_2 control for hospital type and average characteristics of patients treated (i.e. average deprivation of patients, average length of stay) respectively. X_t represents yearly dummies which are intended to capture any contemporaneous shocks that may influence quality.

In any model that includes a lagged dependant variable there is an inherent problem of autocorrelation, which is magnified when the time-series dimension of the data is small (Nickell, 1981). The problem arises because of the correlation of the lagged dependant variable and the error term, and results in making the estimators inconsistent. Including additional regressors does not remove this bias, and if they are correlated with the lagged dependant variable their coefficients may also be seriously biased. This problem can by addressed by estimating a dynamic panel data model, which uses the first differenced Generalized Method of Moments (GMM) estimator (Arellano and Bond, 1991). However, the Arellano-Bond estimator may not perform well if the autoregressive parameters are too large and the time series observations are moderately small. This problem is addressed by the later work of Arellano and Bover (1995) and Blundell and Bond (1998) which impose additional restrictions on the initial conditions process. The Blundell-Bond estimator is used in this analysis, given the small time-series component available in the newly constructed panel dataset.

4 Data

The data used to conduct this analysis was provided by Dr. Foster Intelligence. Dr. Foster is an independent association dedicated to providing high quality health information. One of their products available is a refined version of the cross-sectional database Hospital and Episode Statistics (HES data) that documents hospital activity in England. HES data includes information on all medical and surgical specialties, including private patients treated in NHS hospital trusts. The HES data holds over 15 million patient records each year, stored according the financial year in which the period of care was completed. The data available in the database contains patient characteristic data (e.g. gender, age), clinical information (e.g. diagnoses, procedures undergone) and details of which hospital trust the patient was treated.

While HES data is a rich source of information, it requires some manipulation in order to ensure that the total care received by a patient is measured under the same episode. HES data measures the care received under one consultant during the course of the patient's treated, in the case that the patient is treated by more than one consultant it is important to identify such patients and link their records of care to provide a complete picture of their care experience. Dr. Foster has done the matching within the HES data and is able to provide information on the complete patient experience. In addition they have linked to other data sources such as the death registries, to provide additional information such as death rates at different intervals (30-days and yearly), readmission rates and further details on the patient, such as further information on their co-morbidities and on some socioeconomic characteristics.

Dr. Foster provided data for five conditions (AMI, Stroke, TIA, Congestive Cardiac Failure and Hip Replacement) for the financial years 1996-2008 (Table 1)[1]. In most cases there were problems with the sample sizes of some of the years before 2000, and so these years were not included in the analysis. These conditions were chosen as they require prompt medical attention, they are common in the population and thus provide a large annual sample size to be studied, and most importantly the quality of care provided by the hospital is known to have a significant impact on patient health outcomes (ref). Any hospital trust that had less than 10 admissions throughout the entire period of analysis were dropped from the analysis. Moreover, any primary care trusts, private trusts acting as NHS providers and social care trusts were also excluded.

The main quality outcome measures used in the first model are 30-day mortality rates, designed to measure if a patient dies within up to 30 days after their initial admission to the hospital for treatment (with a value of 1 in the case of death and 0 otherwise), and 28-day readmission rates which measure whether a patient is readmitted for the same condition in a 28 day period (with a value of 1 for readmission and 0 otherwise). Data on gender and age are used as explanatory variables in the analysis, as is a variable indicating whether the treatment undergone was an elective procedure. The Charelson comorbidity index was used to control for severity of patients. This index predicts the 1 year mortality for a patient who may have a range of co-morbid conditions. The index is constructed by assigning a score to each condition depending on the risk of dying associated with it, and summing these scores up. Finally, socio-economic status was measured using the Carstairs index of deprivation. This index is based on four census indicators: low social class, lack of car ownership, overcrowding and male unemployment, which are combined to create a composite score. The deprivation score is divided into seven separate categories which range from very low to very high deprivation.

In the second model of the analysis, the dependent variable used is the filtered outcome quality measure, generated by the first model. The explanatory variables include dummy variables controlling for the type of hospital (whether it is a university

---

[1] AMI data was provided for the years 2000-2008.

hospital, a foundation trust, an acute care trust or a specialist trust). Some other variables were generated from the individual patient level data to control for the patient mix admitted to different trusts, these include the average length of stay of patients, average deprivation of patients, average waiting time for treatment and average number of operations carried out per patient. In addition a variable indicating the number of cases treated by the hospital is included as a proxy for hospital size.

5 Results

This paper examines the measurement of quality at the hospital Trust level using a two-step model described previously. In the first step the unit of analysis is the individual patient. The main focus on interest is the relationship between individual patient's death rates and the quality of the Trust at which they were treated. From this regression the hospital intercepts are extracted and saved, and used as a filtered outcome measure for the second step of the analysis. The coefficients represent the difference in the mean value of 30-day mortality of each hospital benchmarked against a reference hospital, holding patient characteristics constant.

Figure 1 shows the filtered mortality rates extracted from the AMI regression over the years 2000-2008. Each point in the diagram represents an NHS Trust, and indicates their relative mean values. The higher up a hospital trust is on the y-axis the worse its relative performance compared to the other trusts. For all years illustrated, the majority of trusts lie somewhere between 0-0.2. While this does not appear to change substantially in the time period analysed, the amount of fluctuation around this does. In the year 2000 there are many more outliners than in the year 2008, where almost all values are close to the average. The scatterplots for the other conditions, and the other quality measure also show a similar pattern.

(add figure X: scatterplot for readmission for a condition)

The trajectory of the filtered outcome measures over time differs for the individual hospitals, this is illustrated by figures 2 and 3. These figures show the progression over time of the filtered mortality and readmission rates for a random selection of hospitals for each condition included. For each condition the pattern of quality measure across time is different, however within condition across hospitals it is quite similar. Given the values of the mortality rate variable in the data, a higher coefficient indicates a higher mean mortality rate for the trust relative to the benchmark. Thus, a downward trend indicates a relative improvement in quality. Figure 2 suggests that the overall trend in filtered mortality rates indicate that the quality is improving overall, however the scale is quite fine so this quality improvement is quite small. Moreover, the upwards trend is not very clear, apart from the hospitals selected from the Stroke sample.

The trend in filtered readmission rates, illustrated in figure 3, varies between conditions. For patients admitted with congestive cardiac failure, there is a drop in the readmission rate over time for the hospitals selected. For all the other conditions, there is an increase in readmission rates. However, in most cases this trend is not clear and there is considerable fluctuation from year to year. Similarly to the case for the filtered mortality measures, the scale is quite small, indicating that these changes are small in magnitude.

The second step of this model takes these coefficients and tests the fundamental relationships amongst other determinants of hospital quality, such as hospital characteristics and population demographics. These results are presented in tables 1 and 2. The results for the regression testing filtered mortality rates against hospital factors, show that the lags of the dependant variable is significant for all conditions. The sign on the lag coefficient is positive or negative for different conditions. This indicates that quality may be positively or negatively influenced by past performance.

The variables controlling for the type of hospital (foundation trust, specialist trust or university trust) is not always significant. The benchmark comparator is an acute trust. However, the significance levels for the specialist trust in the regressions for AMI and Stroke, suggest that quality is higher at these types of trust for these conditions than at acute hospital trusts. The opposite holds true for university hospitals for the conditions of Stroke and Hip Replacement, where quality is shown to be lower than at acute hospital trusts. For all conditions, except TIA, the number of cases treated is also found to be significant. Generally the more cases treated the higher the quality of care, except for Hip Replacement where the opposite effect is observed. Finally, the controls for patient demographics treated by the hospital are almost never significant (with the exception of the carstairs index in the Hip Replacement model). This is expected as these factors have already been controlled for in the construction of the dependant variable.

Table 3 indicates the regression results for the filtered readmission rates. The results from this regression are similar to those for the filtered mortality rates. The lagged dependant variable is almost always significant, indicating the same path dependency in quality mentioned previously. The number of cases is singnificant in fewer of the conditions (Stroke and Congestive Cardiac Failure) and always with a positive sign, indicating that the more cases treated for these conditions in one hospital results in higher readmission rates. Finally, the same relationship between hospital type and quality is observed, where the more specialised the hospital the lower the readmission, and thus the higher quality.

6 Discussion

This paper has applied a systematic approach for evaluating hospital quality that successfully controls for confounding variables. This approach allows the outcome measures to be more effectively used, as it overcomes some of their main limitations that are encountered when using outcome measures to estimate determinants of hospital level quality. The construction of the filtered outcome indicators allows a better comparison of provider as it removes the confounding patient level variables that are large determinants of outcomes. Filtering out the noise created by these determinants allows the remaining measure to more clearly identify how much of the outcome is associated with the quality of provider.

The second part of the analysis indicates how such a filtered estimate can be used to inform policy. The regression using the filtered outcome indicator suggests that path dependency is a strong determinant of hospital quality. Thus, in order to improve quality a large external shock is necessary to break this cycle. Moreover, in most cases the more specialised a trust is the higher the quality of care provided, in that it is associated with a lower 30-day mortality rate and a lower 28-day readmission rate. Similarly, the more cases a hospital treats of a certain condition, the higher the quality of treatment it provides. This could indicate one of two casual relationships, either hospitals are choosing to specialise in conditions that they are better at providing, or they are better at providing treatment in these conditions because they have more patients with them, and thus more experience.

Finally, the trends in the filtered outcome measures created indicate some overall trends in quality of care in England that could reflect some of the recent reforms being implemented. The filtered mortality measure suggests that since 2000, 30-day mortality rates for AMI, Stroke, TIA, Congestive Cardiac Failure and Hip Replacement have been falling. While the filtered readmission measures indicate that for some of these conditions, especially Stroke, TIA and AMI readmissions have been increasing. While this paper has not used these measures to investigate the possible shocks that could be responsible for these changes, these measures seem to be better suited to measure them than traditional aggregated mortality and/or readmission rates.

References

Arellano, M. and Bond, S. (1991) 'Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations', *Review of Economic Studies*, Vol. 58, No. 2, pp. 277-297.

Arellano, M. and Bover, O. (1995) 'Another look at the instrumental variables estimation of error components models', *Journal of Econometrics*, Vol. 68, pp. 29-52.

Blundell, R and Bond, S. (1998) 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of Econometrics*, Vol. 87, pp. 115-143.

Donabedian, A. (1966). Evaluating the quality of medical care. *Milbank Memorial Fund Quarterly, 44*(3), 166-206.

Iezzoni, L. (forthcoming). Risk adjustment for performance measurement. In P. C. Smith, E. Mossialos, S. Leatherman & I. Papanicolas (Eds.), *Performance measurement for health system improvement: Experiences, challenges and prospects*. Cambridge: Cambridge University Press.

Legido-Quigley, H., McKee, M., Nolte, E and Glinos, IA. (2008) *Assuring the quality of health care in the European Union: A case for action*. Brussels: European Observatory on Health Systems and Policies.

Mant, J. (2001). Process versus outcome indicators in the assessment of quality of health care. *International Journal for Quality in Health Care, 13*(6), 475-480.

McClellan, M. and Staiger, D. (1999) 'The quality of health care providers', *National Bureau of Economic Research Working Paper Series*, Working Paper No. 7327.

Moulton, BR. (1990) 'An illustration of a pitfall in estimating the effects of aggregate variables on micro units', *The Review of Economics and Statistics*, Vol. 72, No. 2, pp. 334-338.

Naylor, C. D., Iron, K., & Handa, K. (2002). Measuring health system performance: problems and opportunities in the era of assessment and accountability. In P. Smith (Ed.), *Measuring up: improving health system performance in OECD countries*. Paris: Organisation for economic co-operation and development.

Nickell, S. (1981) 'Biases in dynamic models with fixed effects', *Econometrica*, Vol. 46, No. 6, pp. 1417-1426.

Power, M. (1999). *The audit society: Rituals of verification*. Oxford: Oxford University Press.

Smith, P. C. (2005). Performance measurement in health care: history, challenges and prospects. *Public Money and Management, 25*(4), 213-220.

Tables and Figures

Table 1: Summary Statistics on the Sample of Patients Included

Condition	Years Analysed	Cases per year	Number of Trusts
AMI	2000-2008	Mean: 864,655 Range: 519,606 -1,113,638	186
Stroke	2000-2008	Mean: 147,983 Range: 80,337-296,035	233
TIA	2000-2008	Mean: 24,180 Range: 17,274-27,759	203
Congestive Cardiac Failure	2000-2008	Mean: 17,708 Range: 10,411-20,946	187
Hip Replacement	1996-2008	Mean: 52,935 Range: 32,265 – 72,251	174

Table 2: Step 2 Regression results for filtered mortality measure

	AMI	Stroke	TIA	Heart	Hip
N (total)	975	1130	1032	920	1674
T (groups)	154	184	168	166	164
Lag1	-0.11663** (0.0386)	0.01415* (0. 0213)	0.17329 ** (0.0509)	0.13110** (0.0575)	-0.19027** (0.0326)
Lag2	-0.21122** (0.3859)	-0.05215** (0.0191)	0.23279** (0.0443)	0.09031* (0.0477)	0.06812** (0.0293)
Cases	-7.82 e-06** (2.53 e-06)	-0.00008** (0.0000)	(0.00004) (0.0000)	-0.00010* (0.0001)	0.00004** (9.91 e-06)
Cases^2	2.69 e-10* (1.45 e-10)	1.15e-08** (2.02e-09)	(2.85e-08) (1.26e-07)	8.50e-09 (5.20e-09)	-2.44e-08** (8.67 e-09)
Average Carstairs	-0.00180 (0.0022)	0.00682 (0.0048)	(-0.00387) (0.0026)	0.00167 (0.0068)	-0.00666** (0.00018)
Average wait time	-0.00002 (0.0000)	-3.32e-07 (3.24e-06)	0.00001 (9.83e-06)	0.00001 (0.0001)	0.00001 (8.15e-06)
Average LOS	0.00033 (0.0002)	-0.0002** (0.0000)	0.00035** (0.0001)	-0.0010 (0.0008)	0.00102** (0.0002)
Average Number of operations	0.01431** (0.0057)	-0.00280 (0.0035)	(0.00020) (0.0025)	-0.0160 (0.0076)	0.00008 (0.0013)
Specialist Trust	-0.41190** (0.0454)	-0.22950** (0.0285)	0.02740 (0.0187)	-0.0160 (0.2640)	0.79515 (0.5573)
Foundation Trust	0.00011 (0.01887)	0.09683** (0.03520)	0.04494 (0.0320)	(0.0027) (0.1586)	0.03848 (0.0058)**
University Hospital	-0.04049 (0.05932)	0.31140** (0.0458)	(-0.00990) (0.0234)	-0.20022 (0.3119)	0.10440** (0.1044)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	0.20888** (0.02215)	0.22470** (0.0286)	-0.0293 (0.0180)	0.3672 (0.0692)	-0.04786** (0.0061)

* Significant at $p \leq 0.1$
** Significant at $p \leq 0.05$
*** Significant at $p \leq 0.01$

Table 3: Step 2 Regression results for filtered readmission measure

	AMI	Stroke	TIA	Heart	Hip
N (total)	975	1109	730	920	1672
T (groups)	154	171	165	166	164
Lag1	0.04903 (0.0453)	0.16448*** (0.0414)	-0.2275*** (0.0570)	0.13110*** (0.0575)	0.1130*** (0.0355)
Lag2	-0.12547*** (0.02113)	0.1027*** (0.0326)	-0.07716* (0.0445)	0.09030* (0.0477)	-0.0271* (0.0295)
Cases	4.78e-07 (1.90e-06)	0.00002*** (8.82e-06)	0.00007 (0.0001)	-0.00010* (0.0001)	0.00003 (0.0000)
$Cases^2$	-6.82e-11 (1.12e-10)	-3.05e-09* (1.65e-09)	-4.91e-08 (1.74e-07)	8.50e-09 (5.20e-09)	-3.06e-08 (2.37e-08)
Average Carstairs	-0.00755*** (0.0018)	0.0052 (0.0038)	-0.0014 (0.0038)	0.00167 (0.0068)	0.0048 (0.0033)
Average wait time	-(.00004** .0000191	2.21e-06 (2.53e-06)	0.00002 (0.0000)	0.0000 (0.0001)	-0.00003 (0.0000)
Average LOS	-8.41e-06 (0.0000)	-0.00012 (0.0001)	0.00044 (0.0004)	-0.00096 (0.0008)	-(0.0004) (0.0005)
Average Number of operations	0.0004 (0.0044)	0.00920*** (0.0028)	-0.01728*** (0.0045)	-0.01596*** (0.0076)	0.0062* (0.0036)
Specialist Trust	-0.00061* (0.0316)	-0.07958*** (0.0223)	0.06634*** (0.0306)	-0.00096 (0.0008)	-0.0240 (0.1356)
Foundation Trust	0.04346 (0.0394)	-0.00325 (0.0595)	0.08996* (0.04971)	0.00266 (0.1586)	-0.0162 (0.0198)
University Hospital	0.09224*** (0.0230)	0.12477*** (0.0472)	-0.06813 (0.0647)	0.2002 (0.3119)	-0.04051* (0.0218)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	0.1837** (0.0207)	-0.01481 (0.0191)	0.13069** (0.0262)	0.36724** (0.0692)	0.17509 (0.0198)***

* Significant at $p \leq 0.1$
** Significant at $p \leq 0.05$
*** Significant at $p \leq 0.01$

Figure 1: Trends in filtered mortality measure for AMI (2000-2008)

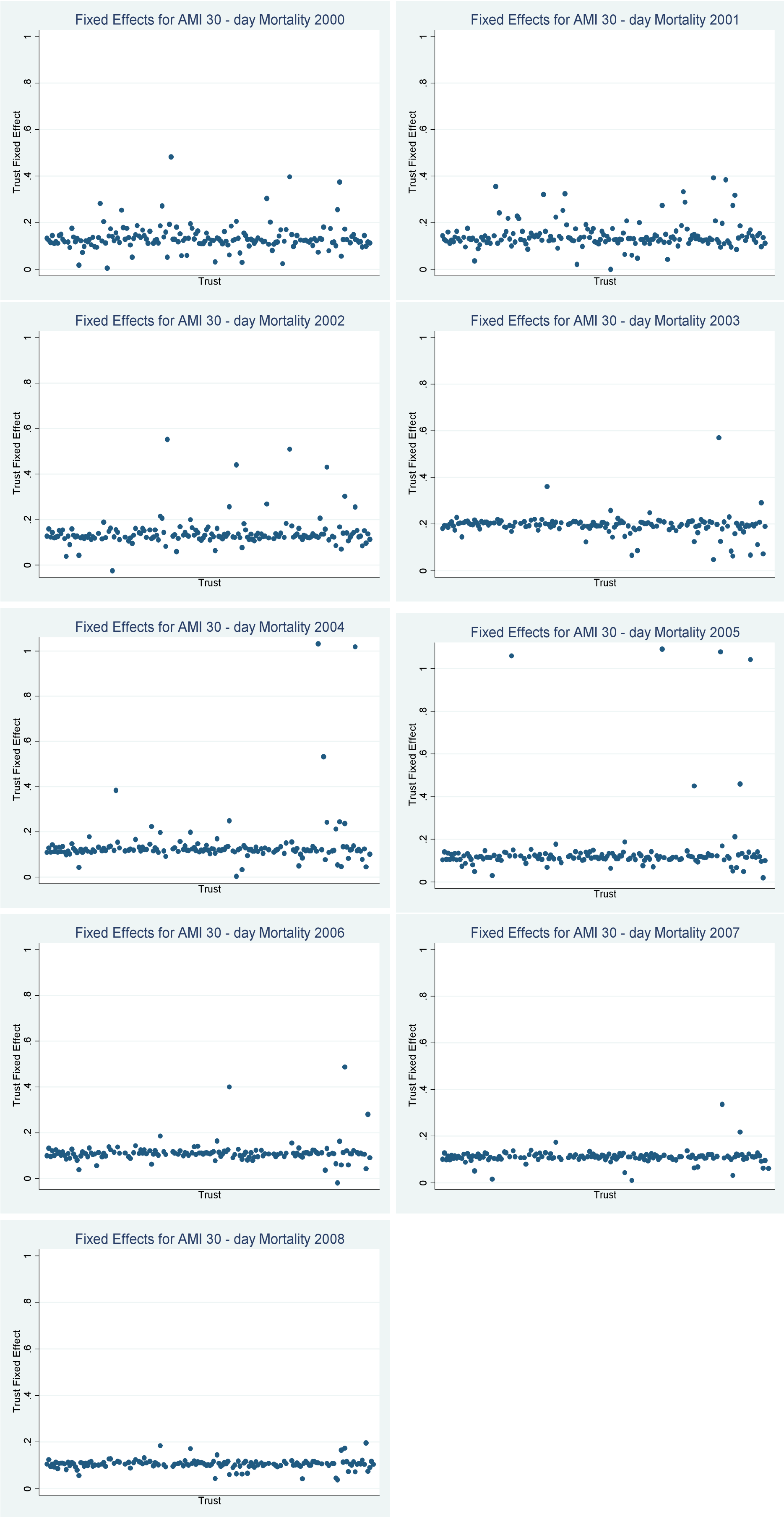

Figure 2: Trends across years in filtered mortality measures for selected hospitals

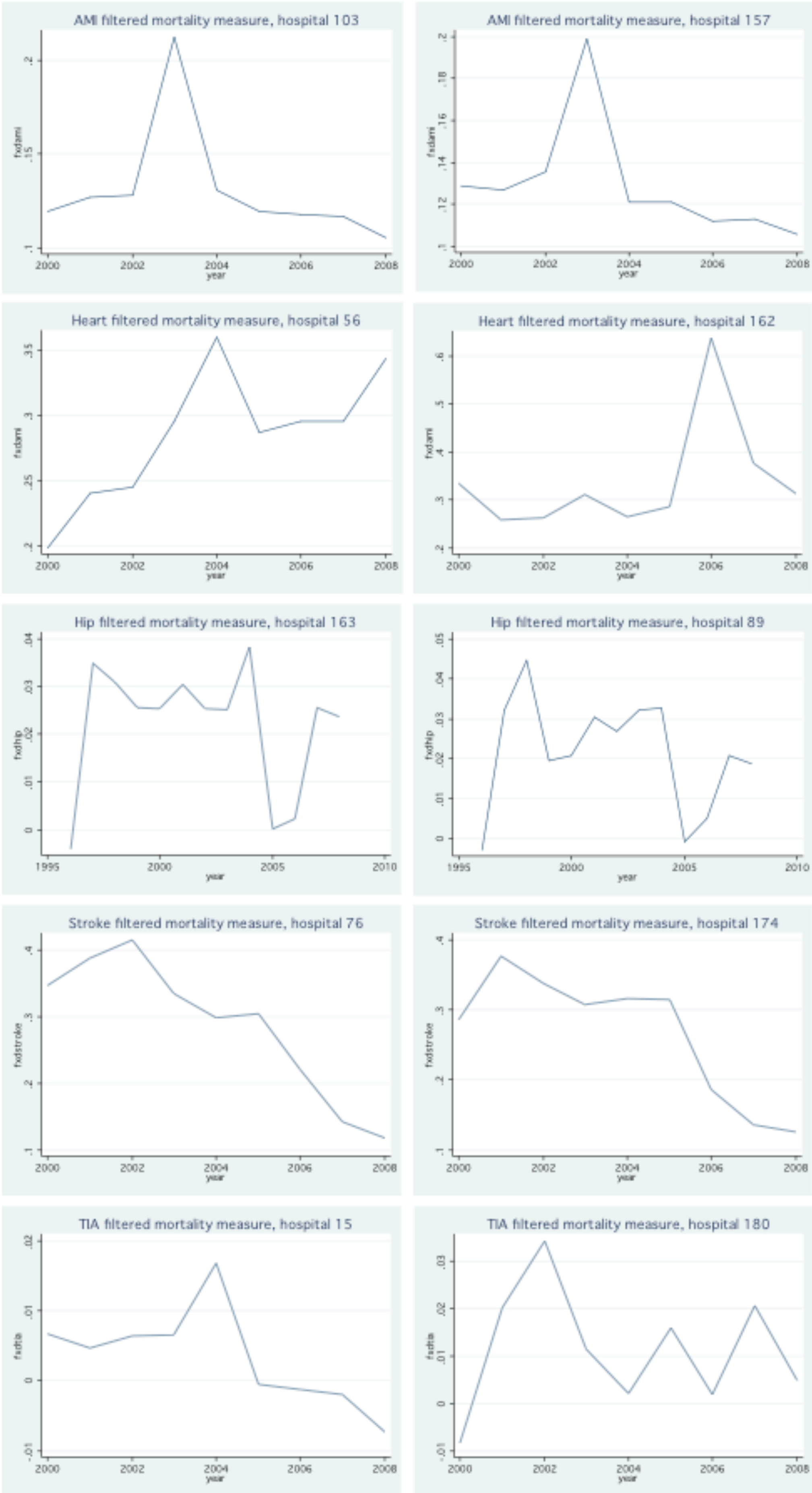

Figure 3: Trends across years in filtered readmission measures for selected hospitals