Methodological report

HSMR 2017

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1. Introduction

This report presents the methods Statistics Netherlands (CBS) has used to calculate the Hospital Standardised Mortality Ratios (HSMRs) for Dutch hospitals. HSMRs are ratios of observed and expected number of deaths and aim to present comparable hospital mortality figures. This chapter gives a general overview of the HSMR. Chapter 2 presents the changes introduced in the method of calculating the HSMR. The methodological aspects of the model used to calculate the HSMRs are described in chapter 3. The model outcomes are evaluated in chapter 4.

1.1 What is the (H)SMR?

Hospital mortality can be measured as the ratio of the number of hospital deaths to the number of hospital admissions (hospital stays) in the same period. This is generally referred to as the "gross mortality rate". Judging hospital performance on the basis of gross mortality rates is unfair, since one hospital may have had more life-threatening cases than another. For this purpose, it is more appropriate to adjust (i.e. standardise) mortality rates across hospitals as much as possible for differences in characteristics of the patients admitted to these hospitals ("case mix"). To this end, the *SMR* (Standardised Mortality Ratio) of a hospital *h* for diagnosis *d* is defined as

$$SMR_{dh} = 100 \times \frac{\text{Observed mortality}_{dh}}{\text{Expected mortality}_{dh}}.$$

The numerator is the *observed* number of deaths with main diagnosis *d* in hospital *h*. The denominator is the *expected* number of deaths for this type of admission under the assumption that individual mortality probabilities (per admission) do *not* depend on the hospital, i.e. are equal to mortality probabilities of identical cases in other hospitals. The denominator is therefore founded on a model based on data from all hospitals, in which the mortality of an admission is explained by characteristics of the patient, such as age, and characteristics of the admission, such as diagnosis and whether the admission is acute and unplanned versus planned. Characteristics of the hospital, such as the number of doctors per bed, are generally not incorporated in the model, since these can be related to the quality of care in the hospitals, which is the intended outcome of the indicator. The model thus produces an expected (estimated) mortality probability for each admission. Adding up these probabilities per hospital gives the total expected mortality over all admissions of that hospital. For each diagnosis *d*, the average SMR_d across the hospitals equals 100 when each hospital is weighted with its (relative) expected mortality.

The *HSMR* of hospital *h* is defined as

$$HSMR_h = 100 \times \frac{\text{Observed mortality in } h}{\text{Expected mortality in } h}.$$

in which both the numerator and denominator are sums across all admissions for all considered diagnoses. The HSMR thus also has a weighted average of 100. As HSMRs may also deviate from 100 only by chance, confidence intervals of the SMRs and HSMRs are calculated so that hospitals can see whether they have a (statistically) significantly high or low adjusted mortality rate compared with the average of 100.

1.2 Purpose of the HSMR

As in many other countries, there is much interest in measuring the quality of health care in the Netherlands. Hospitals can be assessed using various quality indicators, such as the number of medical staff per bed or the availability of certain facilities. However, these indicators do not measure the outcomes of medical performance. A good indicator for the performance of a hospital is the extent to which its patients recover, given the diagnoses and other important characteristics, such as age, sex and comorbidity of the patients. Unfortunately, recovery is hard to measure and mostly takes place after patients have been discharged from the hospital. Although hospital mortality is a much more limited quality indicator, it can be measured accurately. That is why this indicator is now used in several countries, using the HSMR and SMRs as defined in section 1.1. If these instruments were totally valid, i.e. the calculations could adjust perfectly for everything that cannot be influenced by the hospital, a value above 100 would always point to inferior care quality, and the difference between numerator and denominator could be considered an estimate of "avoidable mortality". This would only be possible if the measurement was perfect and mortality by unforeseen complications, after adjustment for differences in case mix, was equally distributed across hospitals. However, it is impossible to construct a perfect instrument to measure the quality of health care. A significantly high (H)SMR will at most be an indication of possible shortcomings in hospital care. But the high value may also be caused by coding errors in the data or the lack of essential covariates in the model related to mortality. Still, a significantly high (H)SMR is often seen as a warning sign, a reason for further investigation into the causes.

1.3 History of the HSMR

In 1999 Jarman initiated the calculation of the (H)SMR for hospitals in England (Jarman et al., 1999). In the following years the model for estimating mortality probabilities was improved by incorporating additional covariates into the model. Analogous models were adopted by some other countries.

In 2005, Jarman started to calculate the (H)SMR for the Netherlands. Later on, these Dutch (H)SMRs were calculated by Kiwa Prismant, in collaboration with Jarman and his colleagues of Imperial College London, Dr Foster Intelligence in London and De Praktijk Index in the Netherlands. Their method is described in Jarman et al. (2010) and was slightly adapted by Prismant (Prismant, 2008) up to reporting year 2009. In 2010 Dutch Hospital Data (DHD, Utrecht), the holder of the national hospital discharge data, asked CBS to calculate the (H)SMRs for the period 2008-2010 and for subsequent years. CBS is an independent public body and familiar with the input data for the HSMR, i.e. the hospital discharge register (LMR: Landelijke Medische Registratie, and its successor LBZ: Landelijke Basisregistratie Ziekenhuiszorg), as it uses this data source for a number of health statistics (see www.statline.cbs.nl).

The starting point for CBS was the HSMR methods previously used by Prismant. As a result of progressive insight CBS has introduced changes in the model for the HSMR 2008-2010 and later years, which are described in the yearly methodological reports (CBS, 2011, 2012, 2013, etc.)

1.4 Confidentiality

Under the Statistics Netherlands Act, CBS is required to keep all data about individuals, households, companies or institutions confidential. Therefore it normally does not deliver recognisable data from institutions to third parties, unless the institutions concerned have stated that they do not have any objections to this. For this reason, CBS needs written permission from all hospitals to deliver their hospital specific (H)SMR figures to DHD. CBS only

supplies DHD with (H)SMR outcomes of hospitals that have granted authorisation to do so. In turn DHD sends each hospital its individual outcome report. Publication of (H)SMR data, which has become mandatory in the Netherlands since 2014 by a regulation of the Dutch Healthcare Authority (NZa), is the responsibility of the hospitals themselves. CBS does not publish data on identifiable hospitals.

1.5 CBS output

CBS estimated the models for expected mortality per diagnosis for the most recent three year period. It calculated the HSMRs and SMRs for all hospitals that (1) had authorised CBS, (2) had registered all or a sufficient part of its admissions in the LBZ in the relevant period, and (3) were not excluded on the grounds of criteria for quality and comparability, which means that the hospital's LBZ data were not too deviant in some respects (see section 3.5).

CBS produces the following output:

1. A hospital-specific report for each hospital, sent via DHD, containing the HSMR and the diagnosis-specific SMR figures for the three year period and the individual years. SMRs are also presented for different patient groups (by age, sex and urgency of admission) and diagnosis clusters. Hospitals can see how they compare with the national average, overall, and per diagnosis and patient group. CBS only made reports for hospitals not excluded under the exclusion criteria and that signed the authorisation request.
2. Each hospital not excluded on the grounds of the exclusion criteria and that signed the authorisation request is provided with a dataset with the mortality probabilities for all its admissions. Besides the probability, each record contains the observed mortality (0 or 1) and the scores on the covariates of the HSMR model. The hospital can use these data for internal investigation.
3. A report on the methods used for calculating the HSMR including the model results and parameters (this document; see www.cbs.nl).

1.6 Limitations of the HSMR

In section 1.2 we argued that the HSMR is not the only indicator to measure hospital care quality. Furthermore, the quality and limitations of the HSMR (and the SMR) instrument are under debate. After all it is based on a statistical model (i.e. the denominator), and a model is always a simplification of reality.

Since the very first publication of the HSMR in England, there has been an on-going debate about the quality of the HSMR as an instrument. Supporters and opponents agree that the HSMR is not a unique, ideal measure, but at most a possible indicator for the quality of health care, alongside other possible indicators. But even if HSMRs were to be used for a more limited purpose, i.e. standardising hospital mortality rates for unwanted side-effects, the interpretation of HSMRs would present various problems, some of which are described briefly below. See also Van Gestel et al. (2012) for an overview.

- Section 3.4 contains the list of covariates included in the regression model. Hospitals do not always code these variables in the same way. Variables such as Age and Sex do not give any problems, but how aspects like acute admissions, main diagnosis and comorbidity are coded may depend on individual physicians and coders. Lilford and Pronovost (2010) argue that if the quality of the source data is insufficient, the regression model should not adjust for such erroneously coded covariates. Our own investigation (Van der Laan, 2013) shows that comorbidities in particular present a

problem in the Netherlands, as there is not much uniformity in coding this covariate (see also section 4.3). Van den Bosch et al. (2010) refer extensively to the influence of coding errors. Nationwide, the registration of comorbidities in Dutch hospitals has increased strongly up to 2014. From 2015 onwards the yearly increase is smaller, but there are still hospitals showing large shifts in the registration of comorbidities. Exclusion criteria for outliers may solve this problem partly but not completely. Another problem is that some hospitals do not (completely) register whether a comorbidity was a complication or not. As complications are excluded from the HSMR comorbidity covariates, differences in registration can have an undesired effect on the HSMR outcomes. To stimulate correct coding of complications an indicator has been added to the HSMR reports sent to the hospitals showing the percentage of registered complications of the hospital, and the overall average. This has led to less underreporting of comorbidities, though there are still considerable differences in the number of complications registered by hospitals.

- Some hospitals may have on average more seriously ill patients than others, even if they have the same set of scores on the covariates. University hospitals may, for example, have more serious cases than other hospitals. It is questionable whether the model adjusts satisfactorily for this phenomenon. Some essential covariates related to mortality are then missing. This may be caused by some of the desired covariates not being measured in the LBZ. Some factors will actually even be hard to measure in this type of routinely collected datasets of all hospital discharges.

- The same problem occurs when certain high risk surgical procedures are only performed in certain hospitals. For instance, open heart surgery only occurs in authorised cardiac centres, and these hospitals may have higher SMRs for heart disease because of the more dangerous interventions. This could be solved by including a covariate in the model that indicates whether such a procedure was performed. This has the disadvantage that a method of treatment is used as a covariate, while ideally it should not be part of the model as it is a component of hospital care.

- Hospital admission and discharge policies may differ. For instance, one hospital may admit the same patient more frequently but for shorter stays than another. Or it may discharge a patient earlier than another because there are adequate external terminal care facilities in the neighbourhood. Also, patients may be referred from one hospital to another for further treatment. Obviously, all these situations influence the outcome of the HSMR, as they influence the observed mortality numbers, but these differences in HSMR cannot be translated in terms of quality of care.

- Hospitals can compare their HSMR and SMRs with the national average of 100. The comparison between (H)SMRs of two or more hospitals with each other is more complicated. There is no complete adjustment for differences in case mix between pairs of hospitals. Theoretically, it is even possible that hospital A has higher SMRs than hospital B for all diagnosis groups, but a lower HSMR. Although this is rather theoretical, bilateral comparison of HSMRs should be undertaken with caution (Heijink et al., 2008).

Some issues in the incomplete correction for differences in the case mix between hospitals may be partly addressed by peer group comparison of (H)SMRs. The calculation of H(SMR)s is still based on the model for all hospitals (without correcting for the type of hospital), but a specialised hospital can then also compare its results with the average for similar hospitals (peer group). For instance, the average HSMR of university hospitals is >100 in the Netherlands, due to insufficient case mix correction, but this still allows these hospitals (and for specific diagnoses also other specialised hospitals) to compare their results with the peer group average.

An indicator including early post-discharge mortality alongside in-hospital mortality could be introduced to tackle the problem of differences in discharge policies (e.g. the availability of terminal care outside hospital), and to some extent referrals between hospitals. Ploemacher *et al*. (2013) saw a decrease in standardised in-hospital mortality in the Netherlands in 2005-2010, which may have been caused by an overall improvement in care quality, but may also be partly explained by substitution of in-hospital mortality by outside-hospital mortality, possibly caused by changes in hospital admission and discharge policies. In cooperation with CBS, Pouw *et al*. (2013) did a retrospective analysis on Dutch hospital data linked to mortality data, and concluded that including early post-discharge mortality is advisable to diminish the effect of discharge bias on the HSMR. In the UK, the SHMI (Summary Hospital-level Mortality Indicator) has been adopted, which includes mortality up to 30 days after discharge (Campbell *et al*., 2011). In 2014, CBS studied the optimal time frame and definition of an indicator including early post-discharge mortality (Van der Laan *et al*., 2015). A fixed period of 45 days after admission in which all mortality is included in the mortality indicator would make the indicator less dependent on hospital discharge policies. A recent French study also recommends fixed post-admission periods of more than 30 days (Lamarche-Vadel et al., 2015).

Although including post-discharge mortality in the indicator would reduce the effect of differences in hospital discharge policies, it would not reduce the effect of differences in admission policies for terminally ill patients. Some hospitals may admit more patients specifically (and sometimes only) for palliative care than other hospitals. As such patients are admitted to die in hospital, not to receive curative care, these admissions may distort HSMR outcomes. Palliative care can be measured in ICD10 (code Z51.5), but this variable should be used with caution, as differences between hospitals in coding practices have been shown in UK and Canada, and adjusting for palliative care may increase the risk of gaming (NHS, 2013; Chong et al., 2012; Bottle et al., 2011). Because of this, and because the LBZ registration does not allow for distinguishing between admissions of terminally ill patients for palliative care only and admissions for curative treatment ending in palliative care, palliative care admissions have not yet been excluded from the calculation of the HSMR in the Netherlands. However, the HSMR reports sent to the hospitals include information on the percentage of the hospital's admissions and deaths related to palliative care as registered in the LBZ compared to the overall average. This may indicate to some extent whether or not palliative care could have biased a hospital's HSMR. However, since the Netherlands also shows a large variation between hospitals in the coding of palliative care, this information should be used with caution.

2. Method changes

This chapter summarizes the changes in the HSMR method (HSMR 2017) compared to the method used last year (HSMR 2016). For previous changes see the respective methodological reports (CBS, 2011, 2012, 2013, 2014, 2015, 2016, 2017).

Overall, the method has remained the same. Only the following minor changes have been implemented:

- Annual update of the covariate *severity of main diagnosis* and linkage of new ICD-10 codes to their historical counterparts :
  The HSMR covariate *severity of main diagnosis* is determined for ICD10 diagnoses using historical mortality, based on six years of LMR/LBZ data not overlapping with the data used for the HSMR calculation. The historical data consists of diagnoses coded either in ICD9 and in ICD10, while the admissions for which the severity has to be determined are all coded in ICD10. Therefore a method was developed last year to calculate the severity for ICD10 main diagnoses, based on a mixed ICD9/ICD10 dataset, ensuring a gradual shift over time from severities based on ICD9 data to severities based solely on ICD10 data. For the current model, the historical data from the LMR/LBZ years 2009-2014 was used (compared to 2008-2013 for the HSMR 2016 model). In addition, for all new ICD10 diagnoses that had been introduced since 2014, Dutch Hospital Data and CBS determined to which ICD9 code, and to which “old” ICD10 code (that was used prior to the introduction of the new ICD10 code), these new codes translated best, so that severity of main diagnosis could also be determined optimally for new codes, using all data in the historical dataset.

- Hospitals are provided with SMRs and 98% confidence intervals for 157 diagnosis groups and several other aggregates and are encouraged to study patient data of diagnosis groups for which observed mortality in their hospital is significantly deviant from expected mortality. In case of multiple significantly high SMRs, hospitals may want to prioritize by first investigating patient data of diagnosis groups with the most marked differences. In order to allow such prioritizing, CBS has provided Dutch Hospital data with p-values of the tests whether the SMRs are significantly high or low. Hospitals can be provided with these p-values by Dutch Hospital Data, if required, and may prioritize their investigation by selecting the diagnosis groups (with significant SMRs) with the lowest p-values.

3. (H)SMR model

Expected hospital mortality - i.e. the denominator of the SMR - has to be determined for each diagnosis group. To this end we use logistic regression models, with mortality as the target (dependent) variable and various variables available in the LBZ as covariates. The regression models for the (H)SMR of a three year period (year t-2 up to year t), and the (H)SMRs of the individual years t-2, t-1 and t, use LBZ data of four years: year t-3 up to year t. The addition an additional year increases the stability and accuracy of the estimates, while keeping the model up to date.

3.1 Target population and dataset

3.1.1 Hospitals

"Hospital" is the primary observation unit. Hospitals report admission data (hospital stay data) in the LBZ. However, not all hospitals participate in the LB. In principle, the HSMR model includes all short-stay hospitals with inpatient admissions participating in the LBZ in the relevant years. The target population of hospitals that qualify for entry in the HSMR-model thus includes all general hospitals, all university hospitals, and short-stay specialised hospitals with inpatient admissions. For a number of partially non-responding hospitals only the fully registered months were included in the model, as in the other months there were indications that fatal cases were registered completely and non-fatal cases partially. The partially registered months of these hospitals were removed from the model as these would otherwise unjustly influence the estimates.

All the above-mentioned hospitals were included in the model, but (H)SMRs were only calculated for hospitals that met the criteria for LBZ participation, data quality and case mix (see section 3.5).

3.1.2 Admissions

We consider both the population of hospitals and the population of admissions. Our target population of admissions consists of "all hospital stays (inpatient admissions) of Dutch residents in Dutch short-stay hospitals in a certain period". The date of discharge, and not the day of admission, determines the year a record is assigned to. So the population of hospital stays of year *t* comprises all inpatient admissions that ended in year *t*. For the sake of convenience, mostly we call these hospital stays "admissions", thus meaning the hospital stay instead of only its beginning. Day admissions are excluded as these are in principle non-life-threatening cases with hardly any mortality. However, from 2015 onwards the new case type "prolonged observations, unplanned, without overnight stay" is included in the HSMR. This case-type was introduced by the Dutch Healthcare Authority, and it replaces the majority of one-day inpatient admissions that were formerly registered. This case type involves more mortality than day cases, and it is therefore relevant to include this in the HSMR.

Lastly, admissions of foreigners are excluded from the HSMR model, partly in the context of possible future modifications of the model, when other data can be linked to admissions of Dutch residents. The number of admissions of foreigners is relatively small.

3.2 Target variable (dependent variable)

The target variable for the regression analysis is the "in-hospital mortality". As this variable is binary, logistic regressions were performed.

3.3 Stratification

Instead of performing one logistic regression for all admissions, we performed a separate logistic regression for each of the diagnosis groups *d*. These sub-populations of admissions are more homogeneous than the entire population. Hence, this stratification may improve the precision of the estimated mortality probabilities. As a result of the stratification, covariates are allowed to have different regression coefficients across diagnosis groups.
The diagnosis groups are clusters of ICD codes registered in the LBZ. Here the main diagnosis of the admission is used, i.e. the main reason for the hospital stay, which is determined at discharge. The basis for the clustering is the CCS *(Clinical Classifications Software*[1]), which clusters ICD diagnoses into 259 clinically meaningful categories. For the HSMR, we further clustered these into 157 diagnosis groups, which are partly the same clusters used for the SHMI (Summary Hospital-level Mortality Indicator) in the UK (HSCIC, 2016).

Therefore, the model includes 157 separate logistic regressions, one for each diagnosis group *d* selected.

In the file "Classification of variables", published together with this report, for each of the 157 diagnosis groups the corresponding CCS group(s) are given, as well as the ICD10 codes of each CCS group.

Apart from the SMRs for each of the 157 diagnosis groups, hospitals also receive SMRs for 17 aggregates of diagnosis groups. This makes it possible to evaluate the SMR outcomes at both the detailed and the aggregated diagnosis level. The 17 main clusters are also given in the "Classification of variables" file. These were derived from the main clusters in the CCS classification of HCUP (see Appendix C1 in), with the following adaptations:

- HCUP main clusters 17 ("Symptoms; signs; and ill-defined conditions and factors influencing health status") and 18 ("Residual codes; unclassified") were merged into one cluster.
- CCS group 54 ("Gout and other crystal arthropathies") is classified in main cluster "Diseases of the musculoskeletal system and connective tissue", and CCS group 57 ("Immunity disorders") is classified in main cluster "Diseases of the blood and blood-forming organs", whereas in the HCUP classification these groups fall in main cluster "Endocrine, nutritional and metabolic diseases, and immunity disorders".
- CCS group 113 ("Late effects of cerebrovascular disease") is classified in main cluster "Diseases of the nervous system and sense organs", whereas in the HCUP classification this group falls in main cluster "Diseases of the circulatory system".
- CCS group 218 ("Liveborn") is classified in main cluster "Complications of pregnancy, childbirth, and the puerperium; liveborn", whereas in the HCUP classification this group falls in main cluster "Certain conditions originating in the perinatal period".

These adaptations are in accordance with the diagnosis groups used for the SHMI (Summary Hospital-level Mortality Indicator) in the United Kingdom (HSCIC, 2016).

[1] *See http://www.hcup-us.ahrq.gov/toolssoftware/ccs10/ccs10.jsp*

Although the names of the main clusters have much similarity with the names of the chapters of the ICD10, there is no one-to-one relation between the two. Although most ICD10 codes of a CCS group do fall within one ICD10 chapter, there often are also codes that fall in other chapters. Especially codes from the R chapter of ICD10 are scattered over several HCUP main clusters.

3.4 Covariates (explanatory variables or predictors of in-hospital mortality)

By including covariates of patient and admission characteristics in the model, the in-hospital mortality is adjusted for these characteristics. As a result, the (H)SMRs are adjusted for these covariates as well. Thus, variables (available in the LBZ) associated with patient in-hospital mortality are chosen as covariates. The more the covariates discriminate between hospitals, the larger the effect on the (H)SMR.

The LBZ variables that are included in the model as covariates are age, sex, socio-economic status, severity of main diagnoses, urgency of admission, Charlson comorbidities, source of admission, year of discharge and month of admission. These variables are described below. For the variables socio-economic status, severity of main diagnosis and source of admission the detailed classifications are presented in the file "Classification of variables", published together with this report.

For the regressions, all categorical covariates are transformed into dummy variables (indicator variables), having scores 0 and 1. A patient scores 1 on a dummy variable if he/she belongs to the corresponding category, and 0 otherwise. As the dummy variables for a covariate are linearly dependent, one dummy variable is left out for each categorical covariate. The corresponding category is the so-called *reference category*. We took the *first* category of each covariate as the reference category.

The general procedure for collapsing categories is described in section 3.6.2. Special (deviant) cases of collapsing are mentioned below.

Age at admission (in years): *0, 1-4, 5-9, 10-14, …, 90-94, 95+*.

Sex of the patient: *male, female.*

If Sex is unknown, "female" was imputed. This is a rare occurrence.

SES (socio-economic status) of the postal area of patient's address: *lowest, below average, average, above average, highest, unknown.*

The SES variable was added to the LBZ dataset on the basis of the postal code of the patient's residence. SES was derived from the Netherlands Institute for Social Research (SCP)[2], which had collected SES data and performed principal component analyses on variables concerning Income, Employment and Education level. Each four-letter postal area was thus assigned a component score. Population-weighted quintiles were calculated from these scores, resulting in the six SES categories mentioned above.

[2] http://www.scp.nl/Onderzoek/Lopend_onderzoek/A_Z_alle_lopende_onderzoeken/Statusscores

Patients for whom the postal area does not exist in the dataset of the SCP (category "unknown"), were added to the category "average" if collapsing was necessary. For 2014-2015 admissions followed the SES classification of 2014, and for 2016-2017 the SES classification of 2016 was used.

Severity of main diagnosis groups: *[0-0.01), [0.01-0.02), [0.02-0.05), [0.05-0.1), [0.1-0.2), [0.2-0.3), [0.3-0.4), [0.4-1], Other*.

This is a categorisation of main diagnoses into mortality rates. Each ICD10 main diagnosis code is classified in one of these groups, as explained below.

A separate model was estimated for each of the 157 diagnosis groups. Most groups have many sub-diagnoses (individual ICD codes), which may differ in seriousness (mortality risk). To classify the severity of the sub-diagnosis, we used the method suggested by Van den Bosch et al. (2011), who suggested categorising the ICD codes into mortality rate categories. To this end, we computed inpatient mortality rates for all ICD sub-diagnoses for six historical LMR years, and chose the following boundaries for the mortality rate intervals: 0, .01, .02, .05, .1, .2, .3, .4 and 1. ("0" means 0 percent mortality; "1" means 100 percent mortality). These boundaries are used for all 157 diagnosis groups. The higher severity categories only occur for a few diagnosis groups.

Six historical LMR/LBZ years are used to determine the classification, not overlapping with the years the HSMR is calculated for as otherwise both are using the same mortality data. The period of the historical dataset shifts every year for each new HSMR calculation, to keep it up to date.

Up to the HSMR 2013-2015, the historical LMR dataset consisted of diagnoses coded in ICD9-CM only, and the severities were also determined for ICD9-CM codes. Main diagnoses registered in ICD10 were converted to ICD9-CM to determine the severity covariate. As In 2012-2013 hospitals transitioned from using ICD9-CM to code the diagnoses of admissions to using ICD10, the diagnoses used for the HSMR 2014-2016 calculation are all coded in ICD10, and the historical dataset used to determine the severities also partly consists of ICD10 coded diagnoses. Therefore, for the HSMR 2014-2016 and later HSMR models, the severities are determined for ICD10 diagnoses. For the HSMR 2015-2017 the severity classification was based on the LMR/LBZ of 2009-2014, which consists of a mix of ICD10 and ICD9-CM data. A method was developed to calculate the severity for ICD10 main diagnoses with such historical datasets, ensuring a gradual shift over time from severities based on ICD9 data to severities based solely on ICD10 data. The method and an investigation of the effects of this change are described in the HSMR 2017 methodological report (CBS, 2017).

For the severity classification the Dutch ICD10-ICD9-CM conversion table was used (table "ICD10 – CvZ80", see http://www.rivm.nl/who-fic/ICD.htm.). As this table had not been updated for recent years, new ICD codes added to the ICD10 in recent years did not have a converted ICD9-CM code or a converted "old" ICD10 code (used prior to the introduction of the new ICD10 code). For these new codes, in consultation with DHD, we added conversions (default counterpart codes in ICD9-CM and ICD10) to the conversion table, to make it complete.

When an ICD10 code and its ICD9-CM equivalent did not occur in the historical dataset, a severity "other" was assigned in the calculation of the (H)SMR. ICD codes that are used by less

than four hospitals and/or have less than 20 admissions also receive a severity of ”other”. The category ”other” contains diagnoses for which it is not possible to accurately determine the severity. If this category “other” needs to be collapsed however, it does not have a natural nearby category. We decided to collapse “other” with the category with the highest frequency (i.e. the mode), if necessary. In the file with regression coefficients (see section 4.5) this will result in a coefficient for “other” equal to that of the category with which “other” is collapsed. The only exceptions are when Comorbidity_17 (Severe liver disease) is collapsed with Comorbidity 9 (Liver disease), and when Comorbidity_11 (Diabetes complications) is collapsed . with Comorbidity 10 (Diabetes). In these cases the regression coefficient of Comorbidity 17/11 is set to zero in the coefficients file, and the coefficient of the less severe analogue (Comorbidity 9/11) should be used for Comorbidity 17/11.

The individual ICD10 codes with the corresponding severity category are available in the separate file “Classification of variables”, published together with this report.

Urgency of the admission: elective, acute.

The definition of an acute admission is: an admission that cannot be postponed as immediate treatment or aid within 24 hours is necessary. Within 24 hours means 24 hours from the moment the specialist decides an acute admission is necessary.

Comorbidity_1 – Comorbidity_17. All these 17 covariates are dummy variables, having categories: *0* (*no*) and *1* (*yes*).

The 17 comorbidity groups are listed in table 3.4.1, with their corresponding ICD10 codes. These are the same comorbidity groups as in the Charlson index. However, separate dummy variable are used for each of the 17 comorbidity groups.

All secondary diagnoses registered in the LBZ and belonging to the 17 comorbidity groups are used, but if a secondary diagnosis is identical to the main diagnosis, it is not considered a comorbidity. Secondary diagnoses registered as a complication arising during the hospital stay are not counted as a comorbidity either.

In conformity with the collapsing procedure for other covariates, comorbidity groups registered in fewer than 50 admissions or that have no deaths are left out, as the two categories of the dummy variable are then collapsed. An exception was made for Comorbidity_17 (Severe liver disease) and Comorbidity_11 (Diabetes complications). Instead of leaving out these covariates in the case of fewer than 50 admissions or no deaths, they are first added to the less severe analogues Comorbidity_9 (Liver diseases) and Comorbidity_10 (Diabetes), respectively. If the combined comorbidities still have fewer than 50 admissions or no deaths, then these are dropped after all.

The ICD10 definitions listed in table 3.4.1 are mostly identical or nearly identical to those of Quan et al. (2005), with some adaptations, which are described in CBS (2014).

Source of admission: *home, nursing home or other institution, hospital.*

This variable indicates the patient’s location before admission.

3.4.1 Comorbidity groups of Charlson index and the corresponding ICD10 codes

No.	Comorbidity groups	ICD10 codes
1	Acute myocardial infarction	I21, I22, I252
2	Congestive heart failure	I50, I110, I130, I132, I255, I42, I43, P290
3	Peripheral vascular disease	I70, I71, I731, I738, I739, I771, I790, I792, K551, K558, K559, Z958, Z959, R02
4	Cerebrovascular disease	G450-G452, G454, G458, G459, G46, I60-I69
5	Dementia	F00-F03, F051, G30, G311
6	Pulmonary disease	J40-J47, J60-J67
7	Connective tissue disorder	M05, M060, M063, M069, M32, M332, M34, M353
8	Peptic ulcer	K25-K28
9	Liver disease	B18, K700-K703, K709, K713-K715, K717, K73, K74, K760, K762-K764, K768, K769, Z944
10	Diabetes	E109, E119, E129, E139, E149
11	Diabetes complications	E100-E108, E110-E118, E120-E128, E130-E138, E140-E148
12	Hemiplegia or paraplegia	G041, G114, G801, G802, G81, G82, G830-G834, G838, G839
13	Renal disease	I120, I131, N01, N03, N052-N057, N18, N19, N25, Z490-Z492, Z940, Z992
14	Cancer	C00-C26, C30-C34, C37-C41, C43, C45-C58, C60-C76, C81-C85, C88, C90-C97
15	HIV	B20-B24
16	Metastatic cancer	C77-C80
17	Severe liver disease	I850, I859, I864, I982, K704, K711, K721, K729, K765, K766, K767

Year of discharge: *2014, 2015, 2016, 2017*.

Inclusion of the year guarantees the number of observed and expected (predicted) deaths to be equal for that year. As a result the yearly (H)SMRs have an average of 100 when weighting the hospitals proportional to their expected mortality.

Month of admission: *January/February, …, November/December*.

The months of admission are combined into 2-month periods.

3.5 Exclusion criteria

Although all hospitals mentioned in section 3.1.1 are included in the model, HSMR outcome data were not produced for all hospitals. HSMRs were only calculated for hospitals that met the criteria for LBZ participation, data quality and case mix. In addition to this, only HSMRs were calculated for hospitals that had authorised CBS to supply their HSMR figures to DHD.
Criteria used for excluding a hospital from calculating HSMRs were:

No inpatient admissions

- Hospitals treating only day cases or outpatients are excluded, as calculation of the HSMR is not relevant for them. In fact, these hospitals do not belong to the HSMR population.

Insufficient participation in the LBZ

- From 2014 onwards, hospitals are required to register all inpatient admissions to get HSMR outcomes. From 2015 onwards this also includes the "prolonged observations, unplanned, without overnight stay".

Data quality

Hospitals are excluded if*:*

- ≤30% of inpatient admissions are coded as acute.
- ≤0.5 secondary diagnoses are registered per inpatient admission, on average per hospital.[3]

Case mix

Hospitals are excluded if:

- Observed mortality is less than 60 in all registered inpatient admissions.

In addition to the above-mentioned criteria, hospitals are also excluded if they had not authorised CBS to supply their HSMR figures.

3.6 Computation of the model and the (H)SMR

3.6.1 SMR and HSMR

According to the first formula in section 1.1, the SMR of hospital *h* for diagnosis *d* is written as

$$SMR_{dh} = 100\,\frac{O_{dh}}{E_{dh}} \tag{3.6.1}$$

with O_{dh} the observed number of deaths with diagnosis *d* in hospital *h*, and E_{dh} the expected number of deaths in a certain period. We can denote these respectively as

$$O_{dh} = \sum_i D_{dhi}, \tag{3.6.2}$$

and

$$E_{dh} = \sum_i \hat{p}_{dhi}, \tag{3.6.3}$$

where D_{dhi} denotes the observed mortality for the i^{th} admission of the combination (*d*,*h*), with scores 1 (death) and 0 (survival), and $\hat{p}_{dhi}$ the mortality probability for this admission, as estimated by the logistic regression of "mortality diagnosis *d*" on the set of covariates mentioned in section 3.4 This gives

$$\hat{p}_{dhi} = \mathrm{Prob}(D_{dhi} = 1|X_{dhi}) = \frac{1}{1+\exp(-\hat{\beta}_d' X_{dhi})}, \tag{3.6.4}$$

with X_{dhi} the scores of admission *i* of hospital *h* on the set of covariates, and $\hat{\beta}_d$ the maximum likelihood estimates of the corresponding regression coefficients, i.e. the so-called log-odds.

[3] For this criterion, all secondary diagnoses are considered, even if they do not belong to the 17 comorbidity groups used as covariates. If identical secondary diagnoses (identical ICD10 codes) are registered within one admission, only one is counted. If a secondary diagnosis is identical to the main diagnosis of the admission, it is not counted as a secondary diagnosis.

For the HSMR of hospital *h*, we have accordingly

$$\mathrm{HSMR}_h = 100\frac{O_h}{E_h} = 100\frac{\sum_d O_{dh}}{\sum_d E_{dh}} = 100\frac{\sum_d \sum_i D_{dhi}}{\sum_d \sum_i \hat{p}_{dhi}}. \tag{3.6.5}$$

It follows from the above formulae that:

$$\mathrm{HSMR}_h = 100\frac{\sum_d E_{dh}\frac{O_{dh}}{E_{dh}}}{E_h} = \sum_d \frac{E_{dh}}{E_h}\mathrm{SMR}_{dh}. \tag{3.6.6}$$

Hence, an HSMR is a weighted mean of the SMRs, with the expected mortalities across diagnoses as the weights.

3.6.2 Modelling and model-diagnostics

We estimated a logistic regression model for each of the 157 CCS diagnosis groups, using the categorical covariates mentioned in section 3.4. Computations were performed using the glm routine of the statistical software R (R Core Team, 2015). Categories, including the reference category, are collapsed if the number of admissions is smaller than 50 or when there are no deaths in the category, to prevent standard errors of the regression coefficients becoming too large. This collapsing is performed starting with the smallest category, which is combined with the smallest nearby category, etc. For variables with only two categories collapsing results in dropping the covariate out of the model (except for comorbidities 17 (Severe liver disease) and 11 (Diabetes complications) which are first combined with comorbidity 9 (Liver disease), and comorbidity 10 (Diabetes), respectively; see section 3.4). Non-significant covariates are preserved in the model, unless the number of admissions is smaller than 50 (or if there are no deaths) for all but one category of a covariate. All regression coefficients are presented in a file published together with this report.

The following statistics are presented to evaluate the models:

- *standard errors* for all regression coefficients (published with the regression coefficients);
- *statistical significance* of the covariates with significance level α=.05, i.e. confidence level .95 (see Appendix);
- *Wald statistics* for the overall effect and the significance testing of categorical variables;
- *C-statistics* for the overall fit. The C-statistic is a measure for the predictive validity of, in our case, a logistic regression. Its maximum value of 1 indicates perfect discriminating power and 0.5 discriminating power not better than expected by chance, which will be the case if no appropriate covariates are found. We present the C-statistics as an evaluation criterion for the logistic regressions.

In addition to these diagnostic measures for the regressions, we present the *average shift in HSMR* by inclusion/deletion of the covariate in/from the model (table 4.4.1). This average absolute difference in HSMR is defined as

$$\frac{1}{N}\sum_{h=1}^{N}\left|\mathrm{HSMR}_h - \mathrm{HSMR}_h^{-x_j}\right|, \tag{3.6.7}$$

where $\mathrm{HSMR}_h^{-x_j}$ is the HSMR that would result from deletion of covariate x_j, and N=81 the total number of hospitals for which an HSMR was calculated..

The Wald statistic is used to test whether the covariates have a significant impact on mortality. But it can also be used as a measure of association. A large value of a Wald statistic points to a strong impact of that covariate on mortality, adjusted for the impact of the other covariates. It is a kind of "explained chi-square". As the number of categories may "benefit" covariates with many categories, it is necessary to also take into account the corresponding numbers of degrees of freedom (df), where the df is the number of categories minus 1. As a result of collapsing the categories, the degrees of freedom can be smaller than the original number of categories minus 1.

A high Wald statistic implies that the covariate's categories discriminate in mortality rates. But if the frequency distribution of the covariate is equal for all hospitals, the covariate would not have any impact on the (H)SMRs. Therefore we also present the change in HSMRs resulting from deleting the covariate. Of course, a covariate that only has low Wald statistics has little impact on the (H)SMRs.

3.6.3 Confidence intervals and control limits

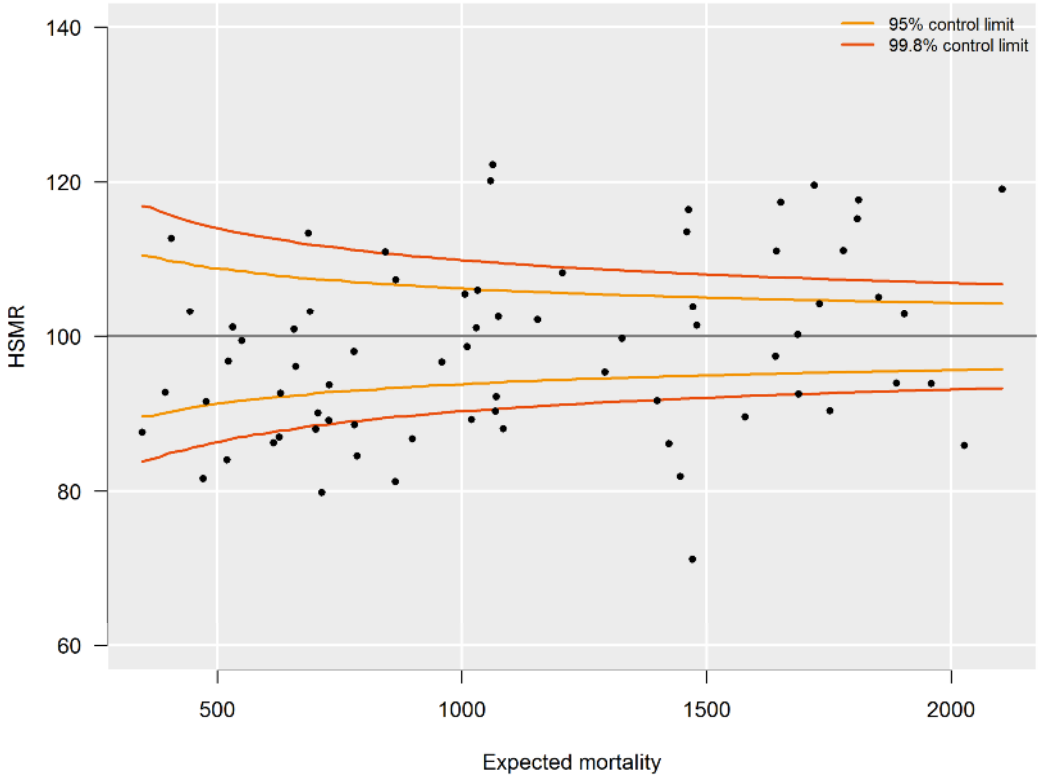
A confidence interval is calculated for each SMR and HSMR, i.e. an upper and lower confidence limit. For the HSMR and most SMRs a confidence level of 95 percent is used, for the SMRs of the 157 diagnosis groups a confidence level of 98 percent is used. These limits are mentioned in the specific reports for the hospitals. A lower limit above 100 indicates a statistically significant high (H)SMR, and an upper limit below 100 a statistically significant low (H)SMR. In the calculation of these confidence intervals, a Poisson distribution is assumed for the numerator of the (H)SMR, while the denominator is assumed to have no variation. This is a good approximation, since the variance of the denominator is small. As a result of these assumptions, we were able to compute exact confidence limits.

HSMRs can be presented in a funnel plot (see figure 3.6.4): a plot of hospitals, where the vertical axis represents the HSMRs and the horizontal axis the expected mortalities. Hospitals located above the horizontal axis (HSMR=100) have a higher than expected mortality. As this might be a non-significant feature, based on chance, control limits are shown in the plot for each possible expected mortality. HSMRs within these control limits do not deviate significantly from 100. In the case of 95 percent control limits, about 2.5 percent of the points would lie above the upper limit if there is no reason for differences between HSMRs, and about 2.5 percent of the points below the lower limit. The same holds, mutatis mutandis, for the 99.8 percent control limits. Here about 0.1 percent of the points would be located above the upper line if there is no reason for differences in standardised mortality rates. Most attention will be paid to this line, as points above this line have a high HSMR that is statistically very significant, which can hardly be the result of chance alone. These hospitals would be advised to investigate the possible reasons for the significantly high values: coding errors, unmeasured case mix variables and/or suboptimal quality of care.

The precision of the HSMR is much greater for a three-year period than for a single year, which is reflected by a smaller range between the control limits. The confidence intervals of the HSMR are also smaller. Of course, drawbacks are that two consecutive three-year figures (e.g. 2014-2016 and 2015-2017) overlap, and that the three-year figure is less up-to-date than the figure of

the last year. Therefore we also calculated the figures for the last available year. Observed mortality (numerator) and expected mortality (denominator) are then calculated for this year's admissions, whereas the expected mortality model of the HSMR still uses the four year data. If a hospital has a significantly high HSMR in the last year, but not in the three year period, this is a signal for further investigation, as the quality of care may have deteriorated.

3.6.4 Funnel plot HSMR (example)



On the other hand, if a hospital has a significantly high HSMR for the three year period, but not in the last year, this does not necessarily mean that the situation has improved in the last year, as the one-year figures are less often significant because of the larger margins. In such cases, not only the significance should be taken into account, but also the HSMR levels over the years.

3.6.5 P-Values

From 2017 onwards, it was decided to also calculate p-values for the SMRs of the 157 diagnosis groups. The reason for this is that high SMRs for diagnosis groups are often an important starting point for further research and hospitals might need an extra tool for prioritizing such research, in case of multiple high SMRs. The p-values can be used when investigating: the lower the p-value the more the observed mortality deviates from the expected mortality. Also, because of the large number of diagnosis groups there is the risk of incorrectly labelling SMRs as significantly high of low (so called type I errors, or false-positives, due to multi-testing). The p-values can also be used to correct for this issue. The p-values are not included in the reports sent to the hospitals, but hospitals can request them from Dutch Hospital Data.

Separate p-values are given for the alternative hypotheses: "the observed mortality (O_{dh}) is higher than the expected mortality (E_{dh})" and "the observed mortality (O_{dh}) is lower than the expected mortality (E_{dh})." The p-values belonging to the these hypotheses are denoted by

$p_{high}(O_{dh})$ and $p_{low}(O_{dh})$ respectively. The main reason for calculating two separate p-values is that by using a confidence of 99 percent for each of the two tests results in the same significant SMRs as found with the 98 percent confidence interval of the SMRs. Another reason is that often the main interest is $p_{high}(O_{dh})$.

The p-value of null-hypothesis "the observed mortality is lower or equal to the expected mortality" is given by the probability of observing a mortality equal to or higher than the observed mortality given the expected mortality:

$$p_{high}(O_{dh}) = \Pr(X \geq O_{dh}|E_{dh}) = 1 - \Pr(X < O_{dh}|E_{dh}). \quad (3.6.8)$$

Assuming that the observed mortality follows a Poisson-distribution with and expected value equal to the expected mortality this is equal to

$$p_{high}(O_{dh}) = 1 - \mathrm{P}_{E_{dh}}(X \leq O_{dh}) + \mathrm{P}_{E_{dh}}(X = O_{dh}), \quad (3.6.9)$$

With $\mathrm{P}_{E_{dh}}(X \leq O_{dh})$ the cumulative distribution function and $\mathrm{P}_{E_{dh}}(X = O_{dh})$ the probability distribution function of the Poisson-distribution with an expected value of E_{dh}.

Likewise the p-value of the null-hypothesis "the observed mortality is higher or equal to the expected mortality" is given by:

$$p_{low}(O_{dh}) = \mathrm{P}_{E_{dh}}(X \leq O_{dh}). \quad (3.6.10)$$

4. Evaluation of the HSMR of 2017

This chapter presents and evaluates the model results. Some summary measures of the 157 logistic regressions are presented, with inpatient mortality as the dependent variable and the variables mentioned in section 3.4 as explanatory variables. More detailed results are presented in the Appendix, and the regression coefficients and their standard errors are presented in the file "Coefficients HSMR 2017.xls", published together with this report.

4.1 Target population and data set

All hospitals that register complete records of inpatient admissions in the LBZ are included in the HSMR model. In 2017 all general and university hospitals were included in the model, as well as two short-stay specialised hospitals (one cancer hospital and one eye hospital). These hospitals were also included in 2014, 2015 and 2016, though the total number of hospitals decreased in this period due to mergers. On the basis of the hospital units in 2017, the total number of hospitals included in the HSMR model of 2014-2017 is 77 and includes 67 general hospitals, 8 university hospitals and 2 short stay specialised hospitals.

For hospitals that did not register all its inpatient records (and the "prolonged observation without overnight stay" records from 2015 onwards) completely, only the completely registered records were included in the model. For some of these hospitals only the fully registered months were included, as in the other months there were indications that fatal cases were registered completely and non-fatal cases partially. The partially registered months of these hospitals were removed from the model as these would otherwise unjustly influence the estimates. For the year 2014 this was done for 1 hospital. In 2015-2017 this did not occur.

Table 4.1.2 lists some characteristics of the admissions included in the HSMR model. Admissions of foreigners were excluded.

4.1.1 Admissions in HSMR model 2014-2017

Excluded admissions of foreigners	32 421
Total number of admissions included in model	7 017 327
Number of inpatient admissions	*6 688 135*
Number of observations	*329 192*
Crude mortality (in admissions in model)	1,9%

4.2 Hospital exclusion

Hospitals were only provided with (H)SMR outcomes if the data fulfilled the criteria stated in paragraph 3.5. In order to qualify for a three-year report (2015-2017) hospitals had to fulfil these criteria for the three consecutive years.

Of the 77 hospitals, the two short stay specialised hospitals and one general hospital had not been asked to grant authorization for providing HSMR numbers because their case mix was very different from that of other hospitals. In fact, all of these hospitals had participated in the LBZ but their data did not meet one or more of the previously stated criteria, such as a minimum number of 60 registered deaths or on average a minimum number of 0.5 comorbidities per

admission. Additionally one general hospital was not provided with a HSMR figure for 2017, because it ended acting independently in the course of 2017 and ceased to have inpatient admissions. All of the other 73 hospitals that had granted authorization fulfilled the criteria and were provided with a HSMR figure for 2017.

For these 73 hospitals the data of 2016 and 2015 was additionally scrutinized in order to determine if a three-year report could be provided. One hospital did not meet one of the criteria in one of those years: this hospital responded partially in the LBZ in 2015. As a result, the data of the other 72 hospitals met the criteria in all years considered and so these hospitals were provided with three-year HSMR figures.

4.3 Impact of the covariates on mortality and HSMR

The table in the appendix shows which covariates have a statistically significant (95 percent confidence) impact on in-hospital mortality for each of the 157 diagnosis groups: "1" indicates (statistical) significance, and "0" non-significance, while a dash (-) means that the covariate has been dropped as the number of admissions is smaller than 50 (or as there are no deaths) for all but one category of a covariate; see section 3.6.2. The last row of the table in the Appendix gives the numbers of significant results across the diagnosis groups for each covariate. These values are presented again in table 4.3.1 below, as a summary, but ordered by the number of times a covariate is significant. Age, urgency of the admission, and severity of the main diagnosis are significant for the great majority of the diagnosis groups. This is also true for several of the comorbidity groups, especially groups 2 and 13, i.e. for Congestive heart failure and Renal disease. Comorbidity 15 is seldom registered as a comorbidity; most diagnosis groups had fewer than 50 admissions with HIV comorbidity. Compared to last year (CBS, 2017) the number of times year of discharge was significant, has dropped from 43 to 27. The year before it already dropped from 72 to 43 (CBS, 2016). The number of models for which comorbidity 10 (diabetes) is significant, has dropped from 44 to 34. For the other covariates the changes are small.

4.3.1 Statistical significance of the covariates for the 157 logistic regressions (summary), HSMR 2017 model.

Covariate	No. of significant results	Covariate	No. of significant results
Age	144	Comorbidity 5	51
Comorbidity 2	128	Comorbidity 17	50
Urgency	127	Sex	45
Comorbidity 13	113	Comorbidity 10	34
Severity main diagnosis	113	Comorbidity 12	30
Comorbidity 9	102	Comorbidity 11	28
Comorbidity 16	101	Year of discharge	27
Comorbidity 3	97	Month of admission	27
Comorbidity 6	89	Comorbidity 7	25
Source of admission	89	Comorbidity 8	15
Comorbidity 14	82	SES	15
Comorbidity 4	75	Comorbidity 15	1
Comorbidity 1	64		

4.3.2 Wald chi-square statistics for the 157 logistic regressions, HSMR 2017 model.

Covariate	Sum of Wald statistics	Sum of df	Covariate	Sum of Wald statistics	Sum of df
Severity main diagnosis	41 651	400	Comorbidity 4	1 469	132
			Month of admission	1 343	781
Age	35 021	2044	Comorbidity 5	1 173	122
Urgency	18 031	156	Comorbidity 1	1 094	147
Comorbidity 2	9 520	144	Sex	952	150
Comorbidity 16	4 715	137	Year of discharge	836	470
Comorbidity 13	4 063	149	SES	796	698
Source of admission	2 930	277	Comorbidity 12	571	102
Comorbidity 3	2 520	145	Comorbidity 10	481	153
Comorbidity 6	2 285	152	Comorbidity 11	408	123
Comorbidity 9	2 177	133	Comorbidity 7	361	122
Comorbidity 14	1 948	145	Comorbidity 8	172	33
Comorbidity 17	1 491	67	Comorbidity 15	29	7

The significance only partially measures the effect of the covariates on mortality. This is better measured using the Wald statistic. Table 4.3.2 presents the total Wald statistics summed over all diagnosis groups for each of the covariates with the respective sum of the degrees of freedom, ordered by value. It shows that severity of main diagnosis has the highest explanatory power. Age and urgency of admission are also important variables. Of the comorbidities comorbidity groups 2, 13, and 16 are the groups with the most impact on mortality. Since two years the impact of year of discharge has dropped when looking at the Wald statistic, from 2409 in the HSMR 2012-2015 model (CBS, 2016) to 836 in the present HSMR 2014-2017 model. This implies that the differences in mortality (corrected for differences in patient characteristics) between the years in the model are decreasing.

As was mentioned in section 3.6.2, when the hospitals differ little on a covariate, the effect of this covariate on the HSMR can still be small even if this covariate is a strong predictor for mortality. Table 0 shows the impact of each covariate on the HSMR, as measured by formula (3.6.7), for the hospitals for which HSMRs are calculated. The comorbidities as a group have the largest effect on the HSMR. This is caused by differences in case mixes between hospitals, but possibly also by differences in coding practice (see Van der Laan, 2013). Notice that we consider the comorbidities as one group here. Deleting Sex hardly has an impact on the HSMRs. Compared to Sex, SES has a reasonable impact on the HSMR 2016. This is because hospitals differ more in terms of SES categories of the postal areas in their vicinity than in terms of the sex distribution of their patients. Overall the differences in the effect of the covariates between this year and the year before are small.

4.3.3 Average shift in HSMR 2017 by inclusion/deletion of covariates

Covariate	Average shift in HSMR	Covariate	Average shift in HSMR
Comorbidity [a)]	6.58	Source of admission	1.18
Age	4.47	SES	0.60
Severity main diagnosis	2.48	Month of admission	0.14
Urgency	2.26	Sex	0.13

a) The comorbidities were deleted as one group and not separately.

4.4 Model evaluation for the 157 regression analyses

Table 4.4.1 presents numbers of admissions and deaths, and C-statistics for the 157 diagnosis groups. The C-statistic is explained in section 3.6.2. Overall the C-statistics have changed little compared to previous year. All changes are smaller than 0.04 with most of them below 0.02. Only two of the 157 diagnosis groups have a C-statistic below 0.70: "Congestive heart failure, nonhypertensive" (70) and "Aspiration pneumonitis; food/vomitus" (84). This was also the case in previous years. For the two diagnosis groups with a C-statistic below 0.7, the model is only partially able to explain patient mortality. This increases the risk that the model does not completely correct for population differences between the hospitals. For the highest scoring diagnosis groups (above 0.9) the covariates strongly reduce the uncertainty in predicting patient mortality.

4.4.1 C-statistics for the logistic regressions of the 157 main diagnosis groups, HSMR 2017 model

Diag. group no.	Description diagnosis group	Number of admissions	Number of deaths	C-statistic
1	Tuberculosis	1 823	39	0.92
2	Septicemia (except in labor)*	22 062	5 601	0.75
3	Bacterial infection; unspecified site	7 412	368	0.81
4	Mycoses	2 289	193	0.82
5	HIV infection	1 241	45	0.84
6	Hepatitis, viral and other infections	28 047	266	0.92
7	Cancer of head and neck	15 473	272	0.88
8	Cancer of esophagus*	11 293	588	0.78
9	Cancer of stomach*	13 282	472	0.79
10	Cancer of colon*	54 937	1 333	0.83
11	Cancer of rectum and anus*	26 832	510	0.85
12	Cancer of liver and intrahepatic bile duct	7 398	414	0.78
13	Cancer of pancreas*	18 040	806	0.80
14	Cancer of other GI organs; peritoneum	7 893	370	0.80
15	Cancer of bronchus; lung*	76 318	4 502	0.84
16	Cancer; other respiratory and intrathoracic	3 337	131	0.87
17	Cancer of bone and connective tissue	8 334	106	0.93
18	Melanomas of skin and other non-epithelial cancer of skin	7 934	82	0.94
19	Cancer of breast*	50 343	416	0.96

20	Cancer of uterus	8 665	119	0.92
21	Cancer of cervix and other female genital organs	12 012	88	0.93
22	Cancer of ovary	10 315	289	0.85
23	Cancer of prostate*	25 720	453	0.91
24	Cancer of testis and other male genital organs	5 973	14	0.95
25	Cancer of bladder*	52 542	445	0.91
26	Cancer of kidney, renal pelvis and other urinary organs	15 552	300	0.88
27	Cancer of brain and nervous system	11 861	256	0.76
28	Cancer of thyroid	5 888	46	0.97
29	Hodgkin`s disease	2 522	35	0.86
30	Non-Hodgkin`s lymphoma*	21 973	922	0.83
31	Leukemias*	23 483	1 178	0.80
32	Multiple myeloma	10 348	495	0.79
33	Cancer; other and unspec. primary; maintenance chemotherapy and radioth.	9 423	167	0.93
34	Secondary malignancies*	85 992	4 308	0.77
35	Malignant neoplasm without specification of site	6 951	498	0.84
36	Neoplasms of unspecified nature or uncertain behavior*	14 078	253	0.86
37	Other and unspecified benign neoplasm	76 801	110	0.89
38	Thyroid and other endocrine disorders	25 909	189	0.91
39	Diabetes mellitus without complication	18 657	102	0.91
40	Diabetes mellitus with complications*	24 914	488	0.85
41	Nutritional deficiencies and other nutritional, endocrine, and metabolic disorders	57 653	413	0.94
42	Fluid and electrolyte disorders*	34 801	797	0.84
43	Cystic fibrosis	2 698	18	0.87
44	Immunity and coagulation disorders, hemorrhagic disorders	12 389	203	0.87
45	Deficiency and other anemia*	47 370	396	0.81
46	Diseases of white blood cells	8 262	184	0.78
47	Mental, affective, anxiety, somatoform, dissociative, and personality disorders	30 957	83	0.87
48	Senility and organic mental disorders	11 897	515	0.74
49	Schizophrenia, mental retardation, preadult disorders and other mental cond.	7 844	21	0.91
50	Other psychoses	4 583	51	0.82
51	Meningitis, encephalitis, and other central nervous system infections	10 323	517	0.89
52	Parkinson`s disease	6 910	76	0.84
53	Multiple sclerosis and other degenerative nervous system conditions	15 814	273	0.90
54	Paralysis and late effects of cerebrovascular disease	4 936	64	0.86
55	Epilepsy and convulsions	48 457	536	0.89
56	Coma, stupor, and brain damage*	3 602	452	0.92
57	Headache and other disorders of the sense organs	87 332	46	0.93
58	Other nervous system disorders	119 463	323	0.97
59	Heart valve disorders*	40 621	1 116	0.78
60	Peri-, endo-, myocarditis, and cardiomyopathy	22 632	627	0.87
61	Essential hypertension, hypertension with compl., and secondary	15 602	136	0.95

	hypertension			
62	Acute myocardial infarction*	132 038	4 232	0.82
63	Coronary atherosclerosis and other heart disease*	163 536	1 081	0.86
64	Nonspecific chest pain	187 759	84	0.88
65	Pulmonary heart disease*	35 480	1 150	0.79
66	Other and ill-defined heart disease	3 431	189	0.83
67	Conduction disorders (heart disease)	23 864	342	0.86
68	Cardiac dysrhythmias*	199 120	971	0.90
69	Cardiac arrest and ventricular fibrillation*	13 178	4 790	0.73
70	Congestive heart failure, nonhypertensive*	118 356	9 601	0.68
71	Acute cerebrovascular disease*	138 709	12 915	0.80
72	Transient cerebral ischemia, and other cerebrovascular disease	51 494	488	0.92
73	Peripheral and visceral atherosclerosis*	38 181	1 847	0.90
74	Aortic and other artery aneurysms*	29 539	2 589	0.89
75	Aortic and arterial embolism or thrombosis*	18 574	487	0.88
76	Other circulatory disease*	35 390	612	0.88
77	Phlebitis, varicose veins, and hemorrhoids	16 492	135	0.91
78	Pneumonia*	143 944	10 903	0.77
79	Influenza	11 015	485	0.83
80	Tonsillitis and upper respiratory infections	95 310	133	0.95
81	Acute bronchitis	27 399	111	0.94
82	Chronic obstructive pulmonary disease and bronchiectasis*	138 780	6 505	0.70
83	Asthma	33 701	101	0.90
84	Aspiration pneumonitis; food/vomitus*	7 520	1 643	0.67
85	Pleurisy; pneumothorax; pulmonary collapse*	26 605	635	0.85
86	Respiratory failure; insufficiency; arrest	8 310	2 505	0.75
87	Lung disease due to external agents	1 928	182	0.78
88	Other lower respiratory disease*	30 025	1 039	0.87
89	Other upper respiratory disease	91 546	657	0.92
90	Intestinal infection	49 326	498	0.90
91	Disorders of mouth, teeth, and jaw	22 244	46	0.97
92	Esophageal disorders	16 592	130	0.91
93	Gastroduodenal ulcer	5 009	221	0.93
94	Gastritis, duodenitis, and other disorders of stomach and duodenum	9 084	78	0.90
95	Appendicitis and other appendiceal conditions	65 668	71	0.97
96	Peritonitis and intestinal abscess	4 785	288	0.85
97	Abdominal hernia	53 701	410	0.93
98	Regional enteritis and ulcerative colitis	19 501	53	0.95
99	Intestinal obstruction without hernia*	33 945	1 597	0.83
100	Diverticulosis and diverticulitis*	40 135	504	0.92
101	Anal and rectal conditions	26 644	50	0.96
102	Biliary tract disease*	146 020	877	0.92
103	Liver disease; alcohol-related*	7 164	866	0.73
104	Other liver diseases*	18 956	959	0.81
105	Pancreatic disorders (not diabetes)	32 116	611	0.85
106	Gastrointestinal hemorrhage*	38 220	1 089	0.81
107	Noninfectious gastroenteritis	25 687	315	0.87

108	Other gastrointestinal disorders*	47 545	693	0.95
109	Nephritis; nephrosis; renal sclerosis	15 390	83	0.91
110	Acute and unspecified renal failure*	17 961	1 110	0.79
111	Chronic kidney disease*	16 110	502	0.89
112	Urinary tract infections*	91 983	2 060	0.80
113	Calculus and other diseases of urinary tract	89 312	198	0.93
114	Genitourinary symptoms and ill-defined conditions	32 238	112	0.89
115	Hyperplasia of prostate and other male genital disorders	46 770	59	0.93
116	Nonmalignant breast conditions	18 422	3	0.99
117	Prolapse and other female genital disorders	76 685	56	0.96
118	Complications of pregnancy, childbirth, and the puerperium; liveborn	659 339	30	0.88
119	Skin and subcutaneous tissue infections	58 255	600	0.90
120	Other skin disorders, chronic ulcer of skin	23 755	235	0.92
121	Infective arthritis and osteomyelitis	13 995	246	0.89
122	Osteoarthritis, rheumatoid arthritis, and other musculoskeletal deformities	259 399	231	0.93
123	Other non-traumatic joint disorders	18 893	51	0.94
124	Spondylosis, back problems, and osteoporosis	99 996	152	0.96
125	Pathological fracture	7 400	93	0.80
126	Other connective tissue disease	56 951	245	0.97
127	Cardiac and circulatory congenital anomalies	10 131	159	0.86
128	Noncardiac congenital anomalies	32 874	224	0.94
129	Short gestation; low birth weight; and fetal growth retardation	64 729	586	0.89
130	Intrauterine hypoxia, perinatal asphyxia, and jaundice	58 679	226	0.94
131	Other perinatal conditions	210 939	238	0.94
132	Joint disorders and dislocations; trauma-related; sprains and strains	39 429	34	0.98
133	Fracture of neck of femur (hip)*	78 992	2 516	0.80
134	Skull and face fractures, spinal cord injury	13 430	219	0.90
135	Fracture of upper limb	53 742	145	0.95
136	Fracture of lower limb	56 152	328	0.94
137	Other fractures	48 537	933	0.87
138	Intracranial injury*	50 471	2 297	0.87
139	Crushing injury or internal injury	24 741	318	0.93
140	Open wounds of head; neck; and trunk	8 013	68	0.89
141	Open wounds of extremities	6 710	41	0.94
142	Complication of device, implant or graft*	100 201	1 306	0.87
143	Complications of surgical procedures or medical care*	105 159	931	0.87
144	Superficial injury; contusion	54 344	438	0.91
145	Burns	4 443	76	0.95
146	Poisoning by psychotropic agents, drugs, or other medications	38 399	293	0.86
147	Other injuries and conditions due to external causes	12 732	646	0.88
148	Syncope	58 298	200	0.86
149	Fever of unknown origin	29 582	192	0.83
150	Lymphadenitis and gangrene	7 428	70	0.94
151	Shock*	1 680	682	0.71
152	Nausea and vomiting	16 476	116	0.85

153	Abdominal pain	66 234	233	0.93
154	Malaise and fatigue	14 871	247	0.81
155	Allergic reactions	12 767	30	0.93
156	Rehabilitation and other aftercare, medical examination/evaluation/screening	146 470	329	0.86
157	Residual codes; unclassified	76 241	339	0.96

*Diagnosis groups present in the HSMR models up to 2014. Diagnosis group 45 then only contained CCS group 59 ("Deficiency and other anemia"); from the HSMR 2015 onwards CCS group 60 ("Acute posthemorrhagic anemia") was added to this group.

4.5 Regression coefficients

The file "coefficients HSMR 2017.xls" contains the estimated regression coefficients (columns "Estimate"), also called "log-odds", for each of the 157 logistic regressions, as well as their standard errors (columns "Std. Err."). The estimated regression coefficients are the elements of the vector $\hat{\beta}_d$ in formula (3.6.4), for each diagnosis *d*. Notice that a β-coefficient has to be interpreted as the difference in log-odds between the category in question and the reference category (first category of the same covariate). For the sake of clarity, the reference categories are given in the first row of the corresponding covariates, and by definition have zero coefficient for each regression.

In many cases categories are collapsed (see section 3.6.2). This results in equal coefficients for the collapsed categories. If all categories were collapsed into one category for a certain variable and for a certain diagnosis group (i.e. if there was only one category with ≥50 admissions and ≥1 death), the variable was dropped from the model and all associated coefficients are set to zero. Therefore, one can directly use the coefficients in the file "coefficients HSMR 2017.xls" to calculate mortality probabilities, with the exception of two of the Charlson comorbidities (Comorbidity 17 and Comorbidity 11). If Charlson comorbidity 17 (Severe liver disease) contains <50 admissions or no mortality, it is collapsed with Charlson comorbidity 9 (Liver disease). In this case the coefficient of Comorbidity 17 is set to zero. When a patient has both comorbidities, it counts as only one comorbidity. Therefore, when the coefficient of Comorbidity 17 is zero in the coefficients file, one should first recode all Charlson 17 comorbidities to Comorbidity 9 and use the coefficient of Comorbidity 9. The same holds for Charlson 11 (Diabetes complications) when it is collapsed with Charlson 10 (Diabetes).

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Appendix. Statistical significance of covariates, HSMR 2017 model

Statistical significance (95% confidence) of the covariates for the 157 logistic regressions (1=significant; 0=non-significant; "-"=variable dropped because all categories are collapsed, due to < 50 admissions or no deaths in all but one category)

No. diagnosis group	Severity main diagnosis	Sex	Age	Urgency	Comorbidity_1	Comorbidity_2	Comorbidity_3	Comorbidity_4	Comorbidity_5	Comorbidity_6	Comorbidity_7	Comorbidity_8	Comorbidity_9	Comorbidity_10	Comorbidity_11	Comorbidity_12	Comorbidity_13	Comorbidity_14	Comorbidity_15	Comorbidity_16	Comorbidity_17	SES	Month admission	Year discharge	Source admission
1	1	0	1	1	-	-	-	-	-	0	-	-	1	0	-	-	0	-	-	-	-	0	0	0	0
2	1	1	1	0	1	1	1	1	1	1	1	0	1	0	0	0	1	1	-	1	1	1	1	0	1
3	1	0	1	0	1	1	1	1	0	0	1	-	1	0	0	1	1	0	-	1	1	0	0	0	0
4	1	0	0	1	0	1	0	-	-	0	0	-	1	0	-	-	1	0	-	1	-	0	0	0	1
5	0	0	0	1	-	-	-	-	-	0	-	-	1	0	-	-	0	0	1	-	-	0	1	0	1
6	1	0	1	1	0	1	0	0	0	1	0	-	1	0	0	0	1	1	0	0	1	0	0	0	1
7	1	0	1	1	0	0	1	1	0	0	0	-	1	0	-	-	0	0	-	1	-	0	0	0	0
8	1	0	0	1	0	1	1	0	0	0	0	-	1	0	0	-	1	0	-	1	-	0	0	0	1
9	0	0	0	1	0	1	1	1	1	1	0	1	0	0	0	-	1	0	-	1	-	0	0	0	1
10	1	1	1	1	1	1	1	1	0	1	0	-	1	1	1	0	1	1	-	1	1	0	0	0	1
11	-	1	1	1	0	1	1	1	0	1	0	-	1	0	0	0	1	0	-	1	-	0	0	0	0
12	0	1	1	1	1	1	1	0	-	0	0	-	1	0	0	-	1	1	-	1	1	0	0	0	0
13	0	0	1	1	0	1	1	1	0	1	0	1	1	0	0	-	1	1	-	1	1	0	0	0	1
14	1	0	1	1	1	1	1	0	-	0	0	-	1	0	1	-	1	0	-	1	-	0	0	0	0
15	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	0	-	1	1	1	0	0	1

16	-	0	0	1	1	-	0	-	-	1	-	-	-	0	-	-	0	0	-	1	-	0	0	0	1
17	0	0	1	1	0	-	0	-	-	0	-	-	-	0	-	0	0	0	-	1	-	0	0	0	1
18	0	0	0	1	0	1	0	0	-	0	1	-	-	0	-	-	0	0	-	1	-	0	0	0	0
19	1	0	1	1	0	1	1	0	0	0	0	-	1	0	0	0	0	0	-	1	-	0	0	0	0
20	0	-	0	1	0	0	-	-	-	0	-	-	-	0	-	-	1	0	-	1	-	0	0	0	0
21	1	-	1	1	0	-	1	-	-	1	0	-	-	0	-	-	1	0	-	1	-	1	0	0	0
22	-	-	1	1	0	0	0	0	-	1	-	-	1	1	-	-	1	0	-	1	-	0	0	0	0
23	-	-	1	1	1	1	1	0	0	1	0	-	1	0	0	1	1	1	-	1	-	0	0	0	0
24	0	-	0	1	0	-	-	-	-	0	-	-	-	0	-	-	-	-	-	1	-	0	0	0	-
25	1	0	1	1	0	1	0	0	0	1	0	-	1	1	0	0	1	0	-	1	-	0	1	0	1
26	0	0	1	1	0	0	0	0	-	1	0	-	1	0	0	0	1	0	-	1	-	0	0	0	0
27	1	0	1	1	0	-	0	1	-	0	0	-	1	1	-	0	1	0	-	1	-	0	0	0	1
28	-	1	1	1	0	-	-	-	-	0	-	-	-	1	-	-	-	0	-	1	-	0	1	0	-
29	0	0	1	1	-	-	-	-	-	0	-	-	-	0	-	-	-	-	-	-	-	0	0	0	-
30	1	0	1	1	1	1	1	1	0	1	0	0	1	0	0	0	1	1	0	1	1	0	0	0	1
31	1	1	1	1	0	1	0	1	0	0	0	-	1	0	0	0	1	1	-	0	1	0	0	0	1
32	0	0	1	1	0	1	1	1	-	1	1	-	0	0	0	0	1	1	-	0	-	0	0	0	0
33	1	0	1	1	1	0	0	-	-	0	-	-	-	0	-	-	0	1	-	1	-	0	0	0	1
34	1	0	1	1	1	1	1	1	0	1	1	1	1	0	1	0	1	1	-	1	1	0	1	1	1
35	0	1	1	1	0	1	1	1	0	1	1	-	1	0	-	-	1	1	-	1	-	0	0	0	1
36	1	0	1	1	0	1	1	1	0	1	0	-	1	0	0	0	1	0	-	1	-	0	0	0	1
37	1	0	1	1	0	1	0	1	0	1	0	-	0	0	0	0	0	0	-	0	0	0	0	0	0
38	1	0	1	1	0	1	1	0	0	0	0	-	1	0	0	0	1	0	-	1	-	0	0	0	1
39	0	0	1	0	0	1	1	1	1	1	0	-	0	0	0	1	0	1	-	0	0	1	0	0	0
40	1	0	1	1	1	1	1	1	0	1	0	-	1	0	0	0	1	1	-	1	-	0	0	0	1
41	1	1	1	1	0	1	0	0	0	0	0	-	0	0	0	0	1	1	-	1	1	1	0	1	1

42	1	1	1	1	0	1	1	1	1	1	0	0	1	0	0	0	0	1	-	1	1	0	1	0	0
43	-	0	0	1	-	-	-	-	-	0	-	-	0	0	-	-	0	-	-	-	0	0	0	0	1
44	1	0	1	1	0	1	1	1	0	0	0	-	0	0	0	0	0	0	-	0	0	0	0	0	1
45	1	0	1	1	0	1	1	1	1	1	0	0	1	0	0	0	1	0	-	1	0	0	0	0	1
46	-	0	1	0	0	1	1	-	-	1	0	-	1	0	-	-	1	0	-	1	-	0	0	0	0
47	1	0	1	0	0	1	0	0	0	0	-	-	1	0	0	0	0	1	-	0	1	0	0	0	0
48	1	1	1	0	1	1	1	0	1	1	0	-	0	0	0	0	1	1	-	0	0	0	0	0	0
49	0	0	0	1	0	1	-	-	0	0	-	-	-	0	-	-	-	0	-	-	-	0	0	0	0
50	-	0	1	0	0	0	1	0	0	1	0	-	0	0	0	-	1	0	-	0	-	0	0	1	0
51	1	0	1	1	0	0	0	1	1	1	0	-	1	0	1	0	1	1	-	1	-	0	0	0	1
52	0	1	1	1	0	0	0	0	0	0	-	-	-	0	-	-	0	0	-	-	-	0	0	1	0
53	1	0	1	1	0	1	0	0	1	0	0	-	-	0	0	0	0	0	-	0	-	0	0	0	1
54	1	0	1	1	0	1	0	0	0	0	-	-	-	0	0	-	0	0	-	0	-	0	0	0	0
55	1	0	1	0	1	1	1	1	1	1	0	-	1	0	0	0	1	1	-	1	1	0	0	0	1
56	1	0	1	1	0	1	1	0	0	1	-	-	1	0	0	0	1	0	-	1	-	0	0	0	1
57	0	0	1	0	0	1	0	0	0	0	0	-	0	0	0	0	0	1	-	0	-	0	0	0	-
58	1	0	1	1	1	1	1	1	0	0	0	-	0	1	0	1	1	1	-	1	1	0	1	0	1
59	1	1	1	1	1	1	1	1	0	1	1	-	1	0	1	0	1	1	-	0	-	0	0	1	1
60	1	1	1	1	1	1	1	1	1	0	0	-	1	0	0	0	1	1	-	1	1	0	0	1	1
61	1	0	1	1	0	1	1	1	0	0	0	-	0	0	1	-	0	0	-	0	-	0	1	0	1
62	1	0	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	0	1	1	0	1	1	1
63	1	0	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	-	1	1	0	0	0	1
64	-	0	1	0	0	0	0	0	0	0	0	-	1	0	0	0	1	1	-	1	-	1	0	1	-
65	1	1	1	1	1	1	1	1	1	1	0	-	1	1	1	1	1	1	-	1	1	0	1	0	1
66	1	0	1	1	1	0	0	0	-	0	-	-	-	0	1	-	1	1	-	-	-	0	0	0	1
67	1	0	1	1	1	1	0	1	1	0	0	-	1	0	0	-	1	1	-	0	-	1	0	0	1

68	1	0	1	1	0	1	1	1	1	1	0	0	1	1	1	1	1	1	-	1	1	1	1	1	1
69	1	1	1	1	1	0	1	1	1	1	1	-	1	1	1	0	1	1	-	1	1	0	0	1	1
70	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	-	1	1	0	1	0	1
71	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-	1	1	0	1	1	1
72	1	0	1	1	1	1	0	1	1	1	0	-	1	0	1	0	1	1	-	1	-	0	0	0	0
73	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	1	1	1	-	1	1	0	0	0	1
74	1	1	1	1	1	1	1	1	1	1	0	-	1	0	0	1	1	0	-	1	-	0	0	0	1
75	1	0	1	1	1	1	1	1	1	1	0	-	1	0	0	0	1	1	-	1	-	0	0	0	1
76	1	0	1	1	1	1	1	1	1	1	1	-	1	0	0	0	1	1	-	1	1	0	0	0	1
77	1	0	1	1	0	1	1	0	0	1	0	-	1	1	0	0	0	1	-	1	0	0	0	0	1
78	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	1	0	1	1	0	1	1	1
79	1	0	1	1	0	1	1	1	0	1	0	-	1	0	1	0	1	1	-	0	-	0	0	1	1
80	1	0	1	1	0	1	0	0	0	1	0	-	0	0	0	1	1	1	-	0	-	0	0	0	1
81	0	0	1	0	0	1	0	1	0	0	0	-	0	0	0	0	1	0	-	0	-	0	0	0	1
82	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	0	1	1	0	1	1	1
83	-	0	1	1	0	1	0	0	1	1	0	-	1	0	0	0	1	1	-	0	-	0	0	0	0
84	-	1	1	0	0	1	1	0	0	0	1	-	1	0	0	0	1	1	-	1	-	0	1	0	0
85	1	0	1	1	1	1	0	0	1	1	0	-	1	0	0	1	1	1	-	1	0	0	0	0	1
86	1	1	1	1	1	0	1	1	1	0	1	-	1	0	0	0	1	1	-	1	-	0	1	0	1
87	1	0	1	1	0	1	0	-	-	0	-	-	-	0	-	-	0	1	-	0	-	0	1	0	1
88	1	1	1	1	1	1	1	1	0	0	0	-	1	0	0	0	1	1	-	1	1	0	0	1	1
89	1	0	1	1	0	1	1	1	0	1	0	-	1	0	0	0	1	1	-	1	0	0	1	1	1
90	1	0	1	1	1	1	1	1	0	1	0	-	1	0	0	0	1	1	-	1	1	0	0	1	1
91	0	0	1	1	0	0	0	0	1	0	0	-	0	0	1	-	1	0	-	1	-	0	1	0	0
92	1	0	1	1	1	1	0	0	0	0	0	0	1	0	0	-	1	0	-	1	0	0	0	0	0
93	1	0	1	0	0	0	1	0	0	1	-	0	1	0	-	-	1	1	-	1	-	1	0	0	0

94	1	0	1	1	0	1	1	0	0	0	-	0	0	0	0	-	0	0	-	0	0	0	0	0	0
95	-	1	1	0	0	1	0	0	0	1	0	-	1	1	-	-	1	0	-	1	-	0	0	0	1
96	1	0	1	1	1	1	0	-	-	1	-	-	1	0	0	-	1	0	-	1	1	0	0	0	1
97	1	1	1	1	1	1	1	1	0	1	0	0	1	1	0	0	1	0	-	1	1	0	0	0	0
98	-	0	1	0	0	1	0	0	-	0	1	-	1	0	-	-	0	0	-	0	-	0	0	0	1
99	1	1	1	1	0	1	1	1	1	1	0	-	1	1	1	0	1	1	-	1	1	1	0	0	1
100	1	0	1	1	0	1	1	1	1	1	1	-	1	0	0	1	1	1	-	1	0	0	0	0	1
101	0	0	1	0	1	1	1	0	0	0	0	-	0	0	0	-	1	1	-	0	-	0	0	1	0
102	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	-	1	1	0	0	0	1
103	1	1	1	1	0	1	1	0	-	0	-	0	1	1	0	-	1	1	-	-	1	0	0	0	1
104	1	0	1	1	0	1	1	0	0	1	0	1	0	1	0	-	1	1	-	1	1	0	0	0	1
105	1	0	1	1	1	1	1	1	0	1	1	1	1	0	0	0	1	1	-	1	1	0	0	0	1
106	1	0	1	1	1	1	1	1	1	1	0	0	1	0	0	0	1	1	-	1	1	1	0	1	1
107	0	0	1	1	0	1	1	0	1	1	0	-	0	0	0	0	0	1	-	1	1	1	0	0	0
108	1	1	1	1	0	1	1	0	1	0	0	0	1	0	0	0	1	1	-	1	0	1	0	1	1
109	1	0	1	1	0	1	1	1	0	0	1	-	0	0	0	0	1	0	-	0	-	0	0	0	1
110	1	1	1	1	1	1	1	0	1	1	0	1	1	0	0	0	0	0	-	1	1	0	1	0	1
111	1	0	1	1	1	1	1	0	1	0	0	-	1	0	0	1	0	1	-	1	-	1	0	0	1
112	1	0	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	-	1	1	0	0	0	1
113	1	1	1	1	1	1	1	1	0	1	0	-	1	0	0	1	1	1	-	1	-	0	0	0	0
114	1	0	1	1	0	0	0	0	1	1	0	-	1	0	0	-	1	1	-	0	-	0	0	0	1
115	1	-	1	1	0	1	0	0	0	1	0	-	1	0	0	0	1	0	-	1	-	0	0	0	0
116	-	-	1	-	1	-	-	-	-	-	-	-	-	0	-	-	0	-	-	-	-	0	0	0	-
117	1	0	1	1	0	1	1	-	0	0	0	-	-	1	0	-	1	0	-	0	-	0	0	0	0
118	1	0	1	1	-	1	0	1	-	-	-	-	1	-	-	-	0	1	-	-	-	0	0	0	0
119	1	0	1	1	1	1	1	1	1	1	0	-	1	1	0	0	1	1	-	1	1	0	1	0	1

120	1	0	1	1	1	1	1	0	0	0	0	-	1	1	0	0	1	0	-	0	-	0	0	0	0
121	1	0	1	1	1	1	0	0	0	0	0	-	1	1	0	0	1	0	-	0	-	0	0	0	1
122	1	0	1	1	1	1	1	1	0	1	0	1	1	1	0	1	1	0	-	1	0	0	0	1	1
123	0	0	1	0	0	1	0	1	0	1	0	-	1	0	0	0	1	0	-	1	-	0	0	0	0
124	1	0	1	1	0	1	1	1	0	1	0	-	0	1	0	1	0	0	-	1	1	0	0	0	0
125	1	1	1	0	0	1	0	0	0	1	1	-	0	1	0	-	1	0	-	0	-	0	0	0	1
126	1	0	1	1	0	1	1	1	0	0	0	-	1	0	0	0	1	1	-	1	-	0	0	0	0
127	1	0	1	0	0	1	0	1	-	0	-	-	-	0	-	-	1	-	-	-	-	0	0	0	0
128	1	0	1	1	-	1	1	-	-	0	-	-	0	0	-	1	0	0	-	-	-	0	0	0	0
129	1	1	-	0	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	1	1
130	1	0	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	0	1
131	1	0	0	1	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	0	1
132	1	1	1	1	0	1	1	0	0	0	-	-	-	0	0	0	0	-	-	-	-	0	0	0	0
133	-	1	1	0	1	1	1	1	1	1	1	-	1	1	1	0	1	1	-	1	1	0	1	0	0
134	1	0	1	1	1	0	0	1	1	0	-	-	0	0	1	0	1	1	-	-	-	0	0	0	0
135	0	1	1	1	0	1	1	1	0	1	0	-	1	0	1	0	1	0	-	0	-	0	0	0	0
136	1	1	1	1	1	1	1	1	1	1	0	-	1	0	1	0	1	0	-	0	-	0	0	0	0
137	1	1	1	1	1	1	1	0	1	1	0	-	1	1	0	1	1	1	-	1	-	0	0	0	0
138	1	1	1	1	1	1	1	1	1	1	0	-	1	0	0	1	1	1	-	1	-	0	0	0	1
139	1	0	1	1	0	1	1	1	1	1	0	-	1	1	0	1	1	0	-	1	-	0	0	0	0
140	1	0	1	0	1	1	0	0	0	1	-	-	1	0	-	-	1	1	-	-	-	0	1	0	0
141	1	0	1	1	0	1	0	-	0	1	0	-	-	0	0	-	0	-	-	-	-	0	0	0	0
142	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	-	1	1	0	1	0	1
143	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	0	1	1	0	1	1	0	1	1	1
144	1	1	1	0	0	1	1	0	1	1	0	-	1	0	1	0	1	1	-	1	-	0	1	0	0
145	1	0	1	1	-	-	1	-	-	1	-	-	-	0	-	-	-	-	-	-	-	0	0	0	0

146	1	1	1	0	1	1	0	1	0	1	0	-	0	0	0	0	0	1	-	0	1	0	0	0	1
147	1	1	1	0	0	1	1	0	1	0	0	-	1	1	1	0	0	0	-	0	-	0	0	0	0
148	-	0	1	0	0	1	1	0	0	1	0	-	0	0	0	0	1	0	-	1	1	0	0	0	0
149	-	0	1	0	1	1	1	0	0	0	0	-	0	0	0	1	1	0	-	1	0	0	0	1	0
150	1	0	1	1	0	1	0	0	0	0	0	-	1	0	0	-	1	0	-	0	-	0	0	0	0
151	-	1	1	0	1	1	1	1	-	1	-	0	1	0	-	-	0	0	-	1	1	0	0	1	0
152	-	0	1	1	0	1	0	0	0	0	0	-	0	0	0	-	0	0	-	1	-	0	0	0	0
153	-	0	1	1	0	1	1	0	1	1	0	0	0	0	0	0	1	1	-	1	1	0	0	0	0
154	-	0	1	1	0	1	0	0	1	0	0	-	1	0	0	1	1	1	-	0	0	0	0	0	1
155	1	0	1	0	0	1	0	-	-	1	-	-	1	0	0	-	1	0	-	0	-	1	0	0	1
156	1	0	1	1	0	1	1	1	0	1	0	-	0	0	0	1	1	1	-	1	1	0	0	1	1
157	1	1	1	1	1	1	1	0	0	0	0	-	0	0	0	0	1	1	-	1	0	0	0	1	1
total	113	45	144	127	64	128	97	75	51	89	25	15	102	34	28	30	113	82	1	101	50	15	27	27	89

The numbers of the comorbidity groups in the header of the table above are the following comorbidities:

Comorbidity_1 - Acute myocardial infarction
Comorbidity_2 - Congestive heart failure
Comorbidity_3 - Peripheral vascular disease
Comorbidity_4 - Cerebral vascular accident
Comorbidity_5 - Dementia
Comorbidity_6 - Pulmonary disease
Comorbidity_7 - Connective tissue disorder
Comorbidity_8 - Peptic ulcer
Comorbidity_9 - Liver disease / Severe liver disease

Comorbidity_9 - Liver disease / Severe liver disease
Comorbidity_10 - Diabetes / Diabetes complications
Comorbidity_11 - Diabetes complications
Comorbidity_12 - Paraplegia
Comorbidity_13 - Renal disease
Comorbidity_14 - Cancer
Comorbidity_15 - HIV
Comorbidity_16 - Metastatic cancer
Comorbidity_17 - Severe liver disease

The names of the diagnosis groups are described in Table 4.4.1, and the corresponding CCS groups and ICD10 codes are given in the file “Classification of variables”, published together with this report.

Explanation of figures

Empty cell	Figure not applicable
.	Figure is unknown, insufficiently reliable or confidential
*	Provisional figure
**	Revised provisional figure
2017–2018	2017 to 2018 inclusive
2017/2018	Average for 2017 to 2018 inclusive
2017/'18	Crop year, financial year, school year, etc., beginning in 2017 and ending in 2018
2015/'16–2017/'18	Crop year, financial year, etc., 2015/'16 to 2017/'18 inclusive

Due to rounding, some totals may not correspond to the sum of the separate figures.

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