Methodological paper

HSMR 2019:

Methodological report

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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 numbers of deaths and aim to present comparable in-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?

In-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 patient characteristics ("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 determined using 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 or not. 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 all 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 are calculated for the SMRs and HSMRs to inform hospitals 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 patient characteristics, such as age, sex and comorbidity. Unfortunately, recovery is hard to measure and mostly takes place after patients have been discharged from the hospital. Although in-hospital mortality is a much more limited quality indicator, it can be measured accurately and is therefore used as a quality indicator 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 indicate inferior quality of care, 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 was equally distributed across hospitals, after adjustment for differences in case mix. 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 a high value may also be caused by coding errors in the data or a lack in the model of essential covariates 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. 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, described in Jarman et al. (2010), was slightly adapted by Prismant (Prismant, 2008) up to reporting year 2009. In 2010 DHD (Dutch Hospital Data, Utrecht), the registry 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 https://opendata.cbs.nl/statline/#/CBS/nl/).

The starting point for CBS was the HSMR method previously used by Prismant. As a result of progressive insight, over the years CBS has introduced changes in the model for the HSMR, which are described in the annual 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 explicitly agree. For this reason, CBS needs written consent 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 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 most recent reporting year and the three-year period. SMRs are also presented for different patient groups (by age, sex and urgency of admission) and diagnosis clusters. Hospitals can compare their outcome with the national average: overall, and per diagnosis and patient group.
2. A dataset for each hospital with the mortality probabilities for all its individual admissions. Besides the probability, each admission record contains the observed mortality (0 or 1) and the scores on the covariates of the HSMR model. Hospitals 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 quality of hospital care. 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), which is always a simplification of reality.

Since the very first publication on the HSMR in the United Kingdom, 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 of 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 in-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 the registration of whether an admission was acute or not, the main discharge diagnosis and comorbidity 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 research (Van der Laan, 2013) shows that comorbidities in particular present a problem in the Netherlands, as there is large variation in coding this covariate (see also section 4.3). Van den Bosch et al. (2010) refer extensively to the influence of coding errors, also Van Erven et al. (2018) report underreporting of comorbidities. 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 annual 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, underreporting complications might falsely lead to a higher comorbidity rate, thus influencing the HSMR outcomes. To stimulate correct coding of complications an indicator has been added to the hospital HSMR reports showing the percentage of registered complications of the hospital, and the overall average. The introduction of this indicator has led to less underreporting of complications, though there are still considerable differences in the number of complications registered by hospitals.

- On average, some hospitals may treat 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 complicated cases than other hospitals, while regional hospitals are generally more involved in end of life care. It is questionable whether the model adjusts satisfactorily for this phenomenon, since some essential information related to mortality is then missing. Some of the desired covariates are not registered in the LBZ and some will actually even be hard to measure at all in this type of registers with routinely collected data of all hospital discharges.

- The same problem occurs when certain high risk surgical procedures are only performed in a selection of 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. The downside however of using a treatment method as a covariate, is that ideally it should not be part of the model as it is a component of hospital care.

- Hospital admission and discharge policies may differ between hospitals. 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 of (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 comparing their results with a peer group average allows these hospitals (and for specific diagnoses also other specialised hospitals) to better interpret their own scores.

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) observed a decrease in standardised in-hospital mortality in the Netherlands in 2005-2010, which may have been caused by an overall improvement in quality of care, 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 date of admission in which all mortality is included in the mortality indicator would make the indicator less dependent on hospital discharge policies. In addition, a French study also recommended 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 (rather than curative care) than other hospitals and those admissions may distort HSMR outcomes. Palliative care can be measured in ICD-10 (code Z51.5), but this variable should be used with caution, as differences between hospitals in coding practices have been shown in e.g. the UK and Canada, and adjusting the HSMR 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 hospital HSMR reports 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.

Despite of the above-mentioned limitations and the ongoing debate on the validity and reliability of mortality measures like the HSMR, there are also studies that suggest that mortality monitoring can be indicative of failings in care quality. Cecil et al. (2020) found that in an English hospital setting mortality alerts, based on higher than expected mortality in 122 diagnosis and procedure groups, were associated with structural indicators of lower quality of

care (e.g. lower nurse-to-bed ratio, overcrowding and financial pressures) and outcome indicators like lower patient and trainee satisfaction. They conclude that their results suggest that there may be value in a mortality alerting system in highlighting poor hospital quality.

2. Method changes

This chapter summarizes the changes in the HSMR method (HSMR 2019) compared to the method used last year (HSMR 2018). For previous changes see the respective methodological reports (CBS, 2011, …, 2019).

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

Exclusion of admissions that do not meet the billing criteria of the Dutch Healthcare Authority (NZa). DHD has asked CBS to remove all admissions from the model that do not meet the NZa criteria for inpatient admissions, and for prolonged observations, unplanned, without overnight stay. Based on the LBZ variables, DHD had marked all admissions in the dataset that did not meet these criteria. These admissions were subsequently removed from the data of all consecutive model years (2016-2019).

A small number of additional ICD-10 codes was allocated to the Charlson comorbidity groups. Over the last couple of years, a number of new ICD-10 codes has been introduced. Admissions with these codes as main diagnosis have been allocated to the appropriate diagnosis groups in the HSMR models, but secondary diagnoses with these new ICD-10 codes were not yet taken into account in the Charlson comorbidity covariates. In case the corresponding older or less detailed ICD-10 code was allocated to a Charlson comorbidity group, the newly introduced ICD-10 code was now also allocated to that Charlson comorbidity group. The following ICD-10 codes were added:

- C86.0-C86.6 (Other specified types of T/NK-cell lymphoma) and D47.5 (Chronic eosinophilic leukaemia [hypereosinophilic syndrome]) were added to Charlson comorbidity group 'Cancer'.
- I98.3* (Oesophageal varices with bleeding in diseases classified elsewhere) was added to Charlson comorbidity group 'Severe liver disease'.
- O98.7 (Human immunodeficiency virus [HIV] disease complicating pregnancy, childbirth and the puerperium) was added to Charlson comorbidity group 'HIV'.
- Z99.4 (Dependence on artificial heart) was added to Charlson comorbidity group 'Peripheral vascular disease'.

The data quality criterion of a minimum value of 0.5 registered secondary diagnoses per inpatient admission, on average per hospital, was increased to 1.5 registered secondary diagnoses. Up till HSMR 2017 a minimum value of 0.5 registered secondary diagnoses was used as a criterion for data quality, but over the years nearly all hospitals had increased their registration of secondary diagnoses up to a point where a minimum value of 0.5 was no longer feasible to indicate (deviant) underreporting. Therefore DHD and CBS decided to increase the minimum vale to 1.5 secondary diagnoses and for HSMR 2019 this new value was used as a formal criterion.

The names of some of the diagnosis and comorbidity groups were adjusted:

- Diagnosis group 116 'Nonmalignant breast conditions' was renamed into 'Non-neoplastic breast conditions'.
- Diagnosis group 149 'Fever of unknown origin' was renamed into 'Fever of other and unknown origin'.

- Main cluster (aggregate of diagnosis groups) ‘Diseases of the genitourinary system’ was renamed into ‘Diseases of the genitourinary system and non-neoplastic breast conditions’.
- Charlson comorbidity group ‘Acute myocardial infarction’ was renamed into ‘Myocardial infarction’.
- Charlson comorbidity group ‘Congestive heart failure’ was renamed into ‘Congestive heart failure and cardiomyopathy’.

Finally, up till HSMR 2014 the model was based on 50 diagnosis groups in which most of the in-hospital mortality occurred. From 2015 onwards all admissions are included in the HSMR, leading to a total number of 157 diagnosis groups. In table 4.4.1 the 50 original diagnosis groups were marked with an asterisk, so that hospitals could compare new outcome with outcome from before 2015. However, after five years of calculating the HSMR over all admissions, this comparison is not relevant anymore. Therefore, the asterisks have been removed from table 4.4.1.

3. (H)SMR model

Expected in-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 to calculate 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, are based on LBZ data of four years: year t-3 up to year t. The addition of an additional year (t-3) increases the stability and accuracy of the estimates, while the moving four-year period up to year t keeps 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 LBZ. 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 that participate in the LBZ. In case of partial non-response by hospitals, only the fully registered months were included in the model, as in the other months fatal cases might be registered completely and non-fatal cases partially. The partially registered months of those hospitals are removed from the model as these might otherwise unjustly influence the estimates. In addition, if for any reason registered data of hospitals in a specific LBZ year had not been not validated by DHD, that year of data is not included in the HSMR model.

All of the above-mentioned hospitals were included in the model, with the exception of the unvalidated 2018 data of two hospitals that had closed in 2018. Data of the short-stay specialised hospital that had started operating as an independent hospital in 2018, were also included. (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 (i.e. inpatient admissions, and prolonged observations, unplanned, without overnight stay) of Dutch residents in Dutch hospitals in a certain period, except admissions that do not meet the billing criteria of the Dutch Healthcare Authority for inpatient admissions and prolonged observations. 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 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 the acute one-day inpatient admissions that had formerly been registered. This case type involves more mortality than day cases, and it is therefore relevant to include this in the HSMR.

Admissions that do not meet the billing criteria of the Dutch healthcare Authority are removed from the data in all consecutive model years. This primarily concerns one-day inpatient admissions where the patient returned home after discharge. Also, about 80 in-hospital deaths where the patient was admitted after 20:00 hrs and died before 24:00 hrs on the same day, were removed from the dataset.

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 259 categories 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 ICD-10 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, 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.

[1] *Clinical Classifications Software is developed for the Healthcare Cost and Utilization Project (HCUP) with the purpose of clustering ICD-codes into clinically meaningful categories, see http://www.hcup-us.ahrq.gov/toolssoftware/ccs10/ccs10.jsp*

- 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).

Although the names of the main clusters are quite similar to the names of the chapters of the ICD-10, there is no one-to-one relation between the two. Although most ICD-10 codes of a CCS group do fall within one ICD-10 chapter, often some of the codes are categorised in other chapters. Especially the codes from the R chapter of ICD-10 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 the main diagnosis, 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 the 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, as registered in the LBZ. SES was derived from the Netherlands Institute for Social Research (SCP), 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.
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 2016-2017 the SES classification of 2016 was used and for 2018-2019 the SES classification of 2017 was used.

Severity of the 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 ICD-10 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 severity (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 occurring ICD sub-diagnoses of the admissions in the current model years, using data of 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 individual ICD codes. The higher severity categories only occur in a few diagnosis groups.

Six historical LMR/LBZ years are used to determine this 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 ICD-9-CM only, and the severities were also determined for ICD-9-CM codes. Main diagnoses registered in ICD-10 were converted to ICD-9-CM to determine the severity covariate. As In 2012-2013 hospitals transitioned from using ICD-9-CM to code the diagnoses of admissions to using ICD-10, the diagnoses used for the HSMR 2014-2016 calculation are all coded in ICD-10, and the historical dataset used to determine the severities also partly consists of ICD-10 coded diagnoses. Therefore, for the HSMR 2014-2016 and later HSMR models, the severities are determined for ICD-10 diagnoses. For the HSMR 2017-2019 the severity classification was based on the LMR/LBZ of 2011-2016, which consists of a mix of ICD-10 and ICD-9-CM data. A method was developed to calculate the severity for ICD-10 main diagnoses with such historical datasets, ensuring a gradual shift over time from severities based on ICD-9 data to severities based solely

on ICD-10 data. The method and an investigation of the effects of this change are described in the HSMR 2017 methodological report (CBS, 2018).

For the severity classification the Dutch ICD-10-ICD-9-CM conversion table was used (table "ICD-10 – CvZ80", see https://www.whofic.nl/downloads-en-links/icd-10). As this table had not been updated for recent years, newly added ICD codes in recent years did not have a converted ICD-9-CM code or a converted "old" ICD-10 code (used prior to the introduction of the new ICD-10 code). For these new codes, in consultation with DHD, we added conversions (default counterpart codes in ICD-9-CM and ICD-10) to the conversion table, to make it complete. When an ICD-10 code and its ICD-9-CM equivalent did not occur in the historical dataset, a severity of "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 ICD-10 codes with the corresponding severity categories 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 medical treatment or aid within 24 hours is necessary. Within 24 hours means 24 hours from the moment the specialist decides that 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 ICD-10 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 ICD-10 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).

3.4.1 Comorbidity groups of Charlson index and the corresponding ICD-10 codes

No.	Comorbidity groups	ICD-10 codes
1	Myocardial infarction	I21, I22, I25.2
2	Congestive heart failure and cardiomyopathy	I50, I11.0, I13.0, I13.2, I25.5, I42, I43, P29.0
3	Peripheral vascular disease	I70, I71, I731, I73.8, I73.9, I77.1, I79.0, I79.2, K55.1, K55.8, K55.9, Z95.8, Z95.9, R02, Z99.4
4	Cerebrovascular disease	G45.0-G45.2, G45.4, G45.8, G45.9, G46, I60-I69
5	Dementia	F00-F03, F05.1, G30, G31.1
6	Pulmonary disease	J40-J47, J60-J67
7	Connective tissue disorder	M05, M06.0, M06.3, M06.9, M32, M33.2, M34, M35.3
8	Peptic ulcer	K25-K28
9	Liver disease	B18, K70.0-K70.3, K70.9, K71.3-K71.5, K71.7, K73, K74, K76.0, K76.2-K76.4, K76.8, K76.9, Z94.4
10	Diabetes	E10.9, E11.9, E12.9, E13.9, E14.9
11	Diabetes complications	E10.0-E10.8, E11.0-E11.8, E12.0-E12.8, E13.0-E13.8, E14.0-E14.8
12	Hemiplegia or paraplegia	G04.1, G11.4, G80.1, G80.2, G81, G82, G83.0-G83.4, G83.8, G83.9
13	Renal disease	I12.0, I13.1, N01, N03, N05.2-N05.7, N18, N19, N25, Z49.0-Z49.2, Z94.0, Z99.2
14	Cancer	C00-C26, C30-C34, C37-C41, C43, C45-C58, C60-C76, C81-C85, C86.0-C86.6, C88, C90-C97, D47.5
15	HIV	B20-B24, O98.7
16	Metastatic cancer	C77-C80
17	Severe liver disease	I85.0, I85.9, I86.4, I98.2, I98.3, K70.4, K71.1, K72.1, K72.9, K76.5, K76.6, K76.7

Source of admission: *home, nursing home or other institution, (other) hospital.*
This variable indicates the patient's location before admission.

Year of discharge: *2016, 2017, 2018, 2019*.
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.
- ≤1.5 secondary diagnoses are registered per inpatient admission, on average per hospital.[2]

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

[2] 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 ICD-10 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.

estimated by the logistic regression of "mortality diagnosis *d*" on the set of covariates mentioned in section 3.4 This gives

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

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

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

It follows from the above formulae that:

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

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

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

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

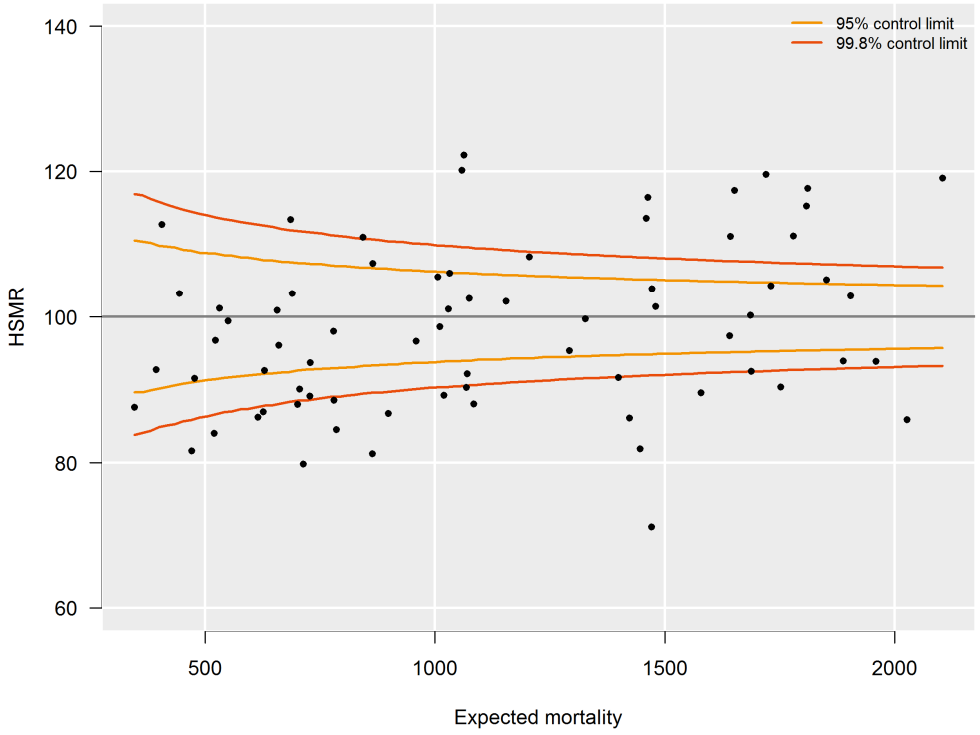
A confidence interval is calculated for each SMR and HSMR, i.e. an upper and lower confidence limit. For the HSMR and most SMRs a confidence level of 95 percent is used, for the SMRs of the 157 diagnosis groups a confidence level of 98 percent is used. These limits are mentioned in the specific reports 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. 2015-2017 and 2016-2018) 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. There can also be other reasons for this, e.g. differences in registration practices over the years, but it is a signal for the hospital for further investigation.

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 2019

This chapter presents and evaluates the model results. Some summary measures of the 157 logistic regressions are presented, with in-hospital 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 2019.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 2019 all general hospitals and university hospitals were included in the model, as well as three short-stay specialised hospitals (two cancer hospitals and an eye hospital). In 2018 two general hospitals were excluded because they had closed in 2018 and the registered data of that year was incomplete and unvalidated. In the period 2016-2019 all of the other hospitals had completely registered inpatient data in the LBZ. For the period 2016-2017 all general and university hospitals were included in the model, and two short-stay specialised hospitals (one cancer hospital and an eye hospital).

Based on the hospital units in 2019 (counting merged hospitals also as one unit in previous years), plus the closed hospitals that were included in the model in previous years, the total number of hospitals included in the HSMR model of 2016-2019 is 78 and includes 67 general hospitals, 8 university hospitals and 3 short stay specialised hospitals.

Table 4.1.1 lists some characteristics of the admissions included in the HSMR model by model year. Admissions not meeting the criteria of the Dutch Healthcare Authority and admissions of foreigners were excluded.

4.1.1 Admissions in HSMR model 2016-2019.

	2016	2017	2018	2019	total
Excluded admissions not meeting the NZa criteria*	39 231	10 600	87 723	138 310	275 864
Excluded admissions of foreigners	8 496	8 631	9 221	9 825	36 173
Total number of admissions included in model	1 774 914	1 718 535	1 647 563	1 636 522	6 777 534
Number of inpatient admissions	*1 665 003*	*1 606 419*	*1 541 992*	*1 523 148*	*6 336 562*
Number of observations	*109 911*	*112 116*	*105 571*	*113 374*	*440 972*
Number of deaths included in model	33 361	32 754	33 417	32 647	132 179
Crude mortality (in admissions in model)	1,9%	1,9%	2,0%	2,0%	2,0%

**Admissions that do not meet the billing criteria of the Dutch Healthcare Authority (NZa) for inpatient admissions, and for prolonged observations, unplanned, without overnight stay. The number of these admissions in the LBZ varies over the years, due to different registration instructions of DHD (e.g. in 2017 hospitals were asked not to register elective one-day inpatient admissions with destination residential environment, rehabilitation facilities or nursing homes in the LBZ).*

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 (2017-2019) hospitals had to fulfil these criteria for the three consecutive years.

Of the 78 hospitals included in the model, 75 had registered (valid) data over 2019. The three other hospitals had closed down during or before 2018. Of the 75 hospitals that had registered complete data in 2019, the three 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 the 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. All of the other 71 hospitals that had granted authorization fulfilled the criteria and were provided with a HSMR figure for 2019.

For these 71 hospitals the data of 2018 and 2017 was additionally investigated in order to determine if a three-year report could be provided. The data of all 71 hospitals met the criteria in all years considered and so all 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.

4.3.1 Statistical significance of the covariates for the 157 logistic regressions (summary), HSMR 2019 model.

Covariate	No. of significant results	Covariate	No. of significant results
Age	141	Comorbidity 1	60
Comorbidity 2	131	Comorbidity 17	50
Urgency	124	Sex	45
Severity main diagnosis	117	Comorbidity 10	43
Comorbidity 13	114	Comorbidity 12	38
Comorbidity 16	105	Month of admission	37
Comorbidity 3	102	Comorbidity 11	24
Comorbidity 9	98	Year of discharge	22
Comorbidity 6	95	Comorbidity 7	20
Source of admission	94	SES	14
Comorbidity 4	82	Comorbidity 8	13
Comorbidity 14	74	Comorbidity 15	1
Comorbidity 5	61		

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 above, 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 a large 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 earlier models (CBS, 2018, 2019) the number of times month of admission was significant, increased from 27 in 2017 to 43 in 2018, but in 2019 it decreased to 37. The number of models in which year of discharge was significant, has dropped over the years: from 72 in the HSMR 2012-2015 model (CBS, 2016) to 22 times in the HSMR 2016-2019 model. Compared to the 2018 model, the largest changes were observed for the covariates Comorbidity 9 (Liver disease, no longer significant in 8 models) and Comorbidity 1 (Myocardial infarction, no longer significant in 7 models). For the other covariates the changes are smaller and the total number of significant covariates only decreased slightly from 1 713 in 2018 to 1 705 in 2019.

4.3.2 Wald chi-square statistics for the 157 logistic regressions, HSMR 2019 model.

Covariate	Sum of Wald statistics	Sum of df	Covariate	Sum of Wald statistics	Sum of df
Severity main diagnosis	42 226	393	Comorbidity 4	1 501	128
Age	33 699	2 005	Comorbidity 5	1 392	120
Urgency	17 740	155	Sex	953	149
Comorbidity 2	10 069	145	Comorbidity 1	952	148
Comorbidity 16	5 052	140	SES	840	695
Comorbidity 13	4 310	148	Comorbidity 12	760	107
Source of admission	3 354	288	Year of discharge	739	469
Comorbidity 3	2 866	146	Comorbidity 10	591	153
Comorbidity 6	2 619	152	Comorbidity 11	368	116
Comorbidity 9	2 148	131	Comorbidity 7	300	125
Comorbidity 14	1 734	145	Comorbidity 8	139	29
Comorbidity 17	1 567	63	Comorbidity 15	20	8
Month of admission	1 523	779			

The significance only partially measures the effect of the covariates on mortality. This is better measured using the Wald statistic. Table 0 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 the main diagnosis has the highest explanatory power. Age and urgency of admission are also important variables. Of the comorbidities in the model, comorbidity groups 2, 16, and 13 are the groups with the most impact on mortality. Compared to the outcome of the 2018 model (CBS, 2019), the order of the covariates is almost identical. When comparing the outcomes of the past 5 models (HSMR 2015 up to HSMR 2019) the explanatory power of year of discharge has decreased with about 70%. This implies that the differences in mortality between the years in the model (corrected for differences in patient characteristics) have decreased. In the HSMR 2019 model the Wald statistics of year of discharge seem to stabilize. The impact of the comorbidities 5 (dementia) and 12 (hemiplegia or

paraplegia) has increased considerably (>50%) over the past five HSMR models. This could be caused by an increased effect of these comorbidities (e.g. the likelihood of dying in hospital when having these conditions has increased), and/or by an increased number of patients with these comorbidities resulting in more accurate estimates of the effect of these comorbidities (which also increases the Wald statistic).

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 4.3.3 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 2019, because hospitals probably 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 and the order of the covariates in table 4.3.3 (ranked by magnitude of the effect) remains unchanged.

4.3.3 Average shift in HSMR 2019 by inclusion/deletion of covariates.

Covariate	Average shift in HSMR	Covariate	Average shift in HSMR
Comorbidity [a)]	6.02	Source of admission	1.44
Age	4.09	SES	0.77
Severity main diagnosis	2.62	Month of admission	0.13
Urgency	1.98	Sex	0.11

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. Apart from the C-statistic of “HIV-infection” that decreased from 0.86 to 0.81 and the C-statistic of “Cystic fibrosis” that increased from 0.88 to 0.93, all other changes are smaller than 0.05 with most of them below 0.02. For 64 diagnosis groups the C-statistic did not change compared to last year.

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 2019 model.

Diag. group no.	Description of diagnosis group	Number of admissions	Number of deaths	C-statistic
1	Tuberculosis	1 836	37	0.90
2	Septicemia (except in labor)	18 190	4 605	0.73
3	Bacterial infection; unspecified site	8 880	475	0.80
4	Mycoses	2 320	196	0.85
5	HIV infection	930	43	0.81
6	Hepatitis, viral and other infections	28 757	258	0.93
7	Cancer of head and neck	15 322	265	0.90
8	Cancer of esophagus	11 861	606	0.82
9	Cancer of stomach	13 205	487	0.81
10	Cancer of colon	51 557	1 273	0.84
11	Cancer of rectum and anus	23 819	468	0.86
12	Cancer of liver and intrahepatic bile duct	7 606	423	0.81
13	Cancer of pancreas	18 990	855	0.82
14	Cancer of other GI organs; peritoneum	8 339	407	0.80
15	Cancer of bronchus; lung	70 779	4 506	0.84
16	Cancer; other respiratory and intrathoracic	3 230	136	0.84
17	Cancer of bone and connective tissue	8 574	89	0.95
18	Melanomas of skin and other non-epithelial cancer of skin	8 049	100	0.94
19	Cancer of breast	45 849	433	0.96
20	Cancer of uterus	8 958	138	0.90
21	Cancer of cervix and other female genital organs	12 448	83	0.93
22	Cancer of ovary	9 617	292	0.85
23	Cancer of prostate	26 255	414	0.92
24	Cancer of testis and other male genital organs	6 838	16	0.89
25	Cancer of bladder	55 252	502	0.92
26	Cancer of kidney, renal pelvis and other urinary organs	16 310	302	0.90
27	Cancer of brain and nervous system	12 038	291	0.79
28	Cancer of thyroid	6 053	49	0.97
29	Hodgkin`s disease	2 293	36	0.88
30	Non-Hodgkin`s lymphoma	22 034	979	0.82
31	Leukemias	22 897	1 227	0.81
32	Multiple myeloma	10 772	489	0.81
33	Cancer; other and unspec. primary; maintenance chemotherapy and radioth.	5 823	141	0.91
34	Secondary malignancies	84 683	4 433	0.77
35	Malignant neoplasm without specification of site	5 281	430	0.85
36	Neoplasms of unspecified nature or uncertain behavior	13 546	234	0.89
37	Other and unspecified benign neoplasm	75 941	107	0.90
38	Thyroid and other endocrine disorders	25 795	202	0.91
39	Diabetes mellitus without complication	16 713	107	0.90
40	Diabetes mellitus with complications	25 188	529	0.86
41	Nutritional deficiencies and other nutritional, endocrine, and metabolic disorders	60 979	472	0.95

42	Fluid and electrolyte disorders	37 415	864	0.84
43	Cystic fibrosis	2 505	12	0.93
44	Immunity and coagulation disorders, hemorrhagic disorders	12 033	203	0.88
45	Deficiency and other anemia	47 300	440	0.82
46	Diseases of white blood cells	8 886	193	0.78
47	Mental, affective, anxiety, somatoform, dissociative, and personality disorders	26 410	79	0.87
48	Senility and organic mental disorders	11 145	494	0.72
49	Schizophrenia, mental retardation, preadult disorders and other mental cond.	7 592	22	0.88
50	Other psychoses	3 869	40	0.85
51	Meningitis, encephalitis, and other central nervous system infections	11 170	534	0.89
52	Parkinson`s disease	6 895	92	0.86
53	Multiple sclerosis and other degenerative nervous system conditions	14 755	268	0.91
54	Paralysis and late effects of cerebrovascular disease	4 592	64	0.86
55	Epilepsy and convulsions	47 582	560	0.90
56	Coma, stupor, and brain damage	2 960	336	0.91
57	Headache and other disorders of the sense organs	78 299	42	0.95
58	Other nervous system disorders	94 605	320	0.96
59	Heart valve disorders	40 560	1 002	0.78
60	Peri-, endo-, myocarditis, and cardiomyopathy	23 393	679	0.88
61	Essential hypertension, hypertension with compl., and secondary hypertension	14 790	119	0.96
62	Acute myocardial infarction	135 811	3 762	0.85
63	Coronary atherosclerosis and other heart disease	142 823	913	0.86
64	Nonspecific chest pain	184 239	59	0.90
65	Pulmonary heart disease	33 890	1 112	0.82
66	Other and ill-defined heart disease	2 353	144	0.89
67	Conduction disorders (heart disease)	25 555	336	0.89
68	Cardiac dysrhythmias	204 589	848	0.90
69	Cardiac arrest and ventricular fibrillation	15 231	5 498	0.75
70	Congestive heart failure, nonhypertensive	124 052	10 047	0.68
71	Acute cerebrovascular disease	148 212	12 859	0.81
72	Transient cerebral ischemia, and other cerebrovascular disease	49 761	406	0.91
73	Peripheral and visceral atherosclerosis	43 764	1 965	0.91
74	Aortic and other artery aneurysms	28 666	2 500	0.89
75	Aortic and arterial embolism or thrombosis	14 703	442	0.88
76	Other circulatory disease	33 165	601	0.87
77	Phlebitis, varicose veins, and hemorrhoids	14 200	128	0.88
78	Pneumonia	147 747	11 701	0.77
79	Influenza	23 406	1 263	0.80
80	Tonsillitis and upper respiratory infections	83 138	136	0.94
81	Acute bronchitis	28 726	101	0.95
82	Chronic obstructive pulmonary disease and bronchiectasis	138 489	7 395	0.70
83	Asthma	32 747	111	0.91
84	Aspiration pneumonitis; food/vomitus	8 593	1 786	0.66

85	Pleurisy; pneumothorax; pulmonary collapse	25 664	624	0.86
86	Respiratory failure; insufficiency; arrest	7 503	2 204	0.75
87	Lung disease due to external agents	1 891	172	0.79
88	Other lower respiratory disease	28 773	977	0.88
89	Other upper respiratory disease	76 675	447	0.92
90	Intestinal infection	57 677	616	0.89
91	Disorders of mouth, teeth, and jaw	22 872	51	0.98
92	Esophageal disorders	15 294	116	0.92
93	Gastroduodenal ulcer	5 070	242	0.93
94	Gastritis, duodenitis, and other disorders of stomach and duodenum	8 336	82	0.89
95	Appendicitis and other appendiceal conditions	67 771	66	0.96
96	Peritonitis and intestinal abscess	4 927	323	0.84
97	Abdominal hernia	51 928	433	0.93
98	Regional enteritis and ulcerative colitis	19 167	50	0.96
99	Intestinal obstruction without hernia	33 819	1 614	0.83
100	Diverticulosis and diverticulitis	38 605	498	0.92
101	Anal and rectal conditions	25 305	38	0.94
102	Biliary tract disease	137 945	971	0.92
103	Liver disease; alcohol-related	7 178	875	0.72
104	Other liver diseases	18 571	979	0.84
105	Pancreatic disorders (not diabetes)	34 567	700	0.85
106	Gastrointestinal hemorrhage	38 858	1 034	0.82
107	Noninfectious gastroenteritis	14 642	214	0.84
108	Other gastrointestinal disorders	44 356	719	0.94
109	Nephritis; nephrosis; renal sclerosis	15 309	92	0.93
110	Acute and unspecified renal failure	17 564	1 055	0.79
111	Chronic kidney disease	15 717	495	0.90
112	Urinary tract infections	99 980	2 469	0.79
113	Calculus and other diseases of urinary tract	89 972	214	0.91
114	Genitourinary symptoms and ill-defined conditions	29 586	112	0.89
115	Hyperplasia of prostate and other male genital disorders	45 968	44	0.94
116	Non-neoplastic breast conditions	18 308	2	1.00
117	Prolapse and other female genital disorders	72 092	39	0.98
118	Complications of pregnancy, childbirth, and the puerperium; liveborn	598 596	18	0.86
119	Skin and subcutaneous tissue infections	59 385	683	0.91
120	Other skin disorders, chronic ulcer of skin	21 439	231	0.93
121	Infective arthritis and osteomyelitis	14 232	269	0.89
122	Osteoarthritis, rheumatoid arthritis, and other musculoskeletal deformities	259 822	199	0.92
123	Other non-traumatic joint disorders	15 718	45	0.94
124	Spondylosis, back problems, and osteoporosis	96 284	181	0.98
125	Pathological fracture	6 286	89	0.81
126	Other connective tissue disease	47 459	257	0.97
127	Cardiac and circulatory congenital anomalies	9 637	186	0.88
128	Noncardiac congenital anomalies	30 079	224	0.95
129	Short gestation; low birth weight; and fetal growth retardation	67 406	478	0.91

130	Intrauterine hypoxia, perinatal asphyxia, and jaundice	58 270	224	0.94
131	Other perinatal conditions	212 810	237	0.94
132	Joint disorders and dislocations; trauma-related; sprains and strains	33 668	38	0.98
133	Fracture of neck of femur (hip)	82 861	2 641	0.81
134	Skull and face fractures, spinal cord injury	13 264	237	0.89
135	Fracture of upper limb	49 324	155	0.95
136	Fracture of lower limb	54 366	296	0.95
137	Other fractures	47 566	992	0.87
138	Intracranial injury	43 167	2 412	0.82
139	Crushing injury or internal injury	23 387	415	0.92
140	Open wounds of head; neck; and trunk	7 126	55	0.89
141	Open wounds of extremities	6 167	39	0.93
142	Complication of device, implant or graft	102 193	1 331	0.88
143	Complications of surgical procedures or medical care	107 333	838	0.87
144	Superficial injury; contusion	63 079	507	0.92
145	Burns	4 139	99	0.95
146	Poisoning by psychotropic agents, drugs, or other medications	38 647	313	0.88
147	Other injuries and conditions due to external causes	13 060	627	0.89
148	Syncope	53 332	154	0.88
149	Fever of other and unknown origin	26 217	163	0.85
150	Lymphadenitis and gangrene	5 680	37	0.95
151	Shock	1 341	502	0.72
152	Nausea and vomiting	15 057	95	0.84
153	Abdominal pain	55 626	168	0.95
154	Malaise and fatigue	12 225	180	0.82
155	Allergic reactions	13 014	34	0.98
156	Rehabilitation and other aftercare, medical examination/evaluation/screening	110 837	227	0.87
157	Residual codes; unclassified	71 122	174	0.95

4.5 Regression coefficients

The file “coefficients HSMR 2019.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 2019.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 2019 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	0	-	-	-	-	-	0	-	-	1	0	-	-	1	-	-	-	-	0	0	0	1
2	1	1	1	0	1	1	1	1	1	1	0	0	1	0	0	0	1	1	-	1	1	0	1	0	1
3	1	1	1	0	1	1	0	1	0	1	1	-	1	0	0	1	1	1	-	1	1	0	1	0	0
4	1	0	1	1	0	1	0	-	-	0	0	-	1	0	-	-	1	0	-	1	-	0	1	0	1
5	0	0	0	1	-	-	-	-	-	0	-	-	0	0	-	-	-	0	1	-	-	0	0	0	1
6	1	0	1	1	0	1	0	1	1	1	0	-	1	0	0	1	1	1	0	0	1	0	0	0	1
7	1	0	1	1	0	0	1	1	1	0	0	-	1	1	-	-	0	0	-	1	-	0	0	0	0
8	1	0	0	1	0	1	1	0	0	1	0	-	1	0	0	-	1	0	-	1	-	0	1	0	1
9	0	0	1	1	0	1	0	1	1	1	0	1	1	0	0	-	1	0	-	1	-	0	0	0	0
10	1	1	1	1	1	1	1	1	1	1	0	-	1	1	1	0	1	1	-	1	1	0	0	0	1
11	0	0	1	1	0	1	0	0	1	1	0	-	1	0	0	0	1	0	-	1	-	0	0	0	0
12	0	0	1	1	0	0	1	-	-	0	0	-	0	0	0	-	1	0	-	1	1	0	1	0	0
13	0	0	1	1	0	1	1	1	0	1	0	1	1	0	1	-	1	1	-	1	1	0	0	0	1
14	1	0	1	1	0	1	0	0	-	1	0	-	1	1	0	-	1	0	-	1	-	0	0	0	0
15	1	1	1	1	1	1	1	1	0	1	1	-	1	1	0	0	1	1	-	1	1	0	0	0	1

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

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

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

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

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

146	1	0	1	0	0	1	1	1	0	1	0	-	1	0	1	0	0	0	-	0	1	0	0	0	1
147	1	0	1	1	0	1	1	0	0	0	0	-	1	0	0	0	1	0	-	0	-	0	0	0	1
148	-	0	1	0	0	1	1	0	0	1	0	-	0	0	0	0	1	1	-	1	1	0	1	0	0
149	-	0	1	0	1	1	1	1	0	0	0	-	0	1	0	0	1	1	-	1	-	0	0	1	0
150	1	1	1	1	1	0	0	-	0	0	0	-	-	0	0	-	1	0	-	0	-	0	0	0	0
151	1	1	1	0	1	0	1	-	-	0	-	-	1	0	-	-	0	0	-	0	-	0	1	0	1
152	-	0	1	0	0	1	0	0	0	0	0	-	0	0	0	0	0	0	-	1	-	0	0	0	0
153	1	0	1	1	0	1	1	1	1	1	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	0	-	1	-	0	0	0	0
155	1	0	1	1	0	1	0	-	-	1	0	-	1	0	0	-	0	0	-	0	-	0	1	0	0
156	0	0	1	1	0	1	1	1	0	1	0	-	1	0	0	1	1	1	-	1	1	0	0	0	1
157	1	1	1	1	0	1	1	0	0	0	0	-	1	0	0	1	1	1	-	1	0	0	0	0	1
total	117	45	141	124	60	131	102	82	61	95	20	13	98	43	24	38	114	74	1	105	50	14	37	22	94

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

Comorbidity 1 - Myocardial infarction
Comorbidity 2 - Congestive heart failure and cardiomyopathy
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
Comorbidity 10 - Diabetes
Comorbidity 11 - Diabetes complications
Comorbidity 12 - Hemiplegia or 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 ICD-10 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
2019–2020	2019 to 2020 inclusive
2019/2020	Average for 2019 to 2020 inclusive
2019/2020	Crop year, financial year, school year, etc., beginning in 2019 and ending in 2020
2017/18–2019/20	Crop year, financial year, etc., 2017/18 to 2019/20 inclusive

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

Colophon

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