Methodological paper

HSMR 2020:

Methodological report

Jan van der Laan
Sigrid van Hoek
Corine Witvliet-Penning
Agnes de Bruin

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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 in-hospital mortality figures in comparison to the national average. 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. In chapter 5 additional analyses are presented, investigating the possible impact of the COVID-19 pandemic on the HSMR outcomes of 2020. Conclusions are given in chapter 6.

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. Therefore it is more appropriate to adjust (i.e. standardise) mortality rates for differences in patient characteristics (”case mix”) across hospitals as much as possible. 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 national hospitals, in which the in-hospital mortality is explained by patient characteristics, such as age and diagnosis, and characteristics of the admission, such as 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 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 SMRd 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 by chance only, 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 value 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. Various quality indicators are available, 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 occurs 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 would 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 unforeseeable complications was equally distributed across hospitals, after adjustment for differences in case mix. However, it is impossible to construct such a perfect instrument to measure the quality of health care; the outcome of the indicator will to some extent always be partially influenced by differences between hospitals with regard to case mix, availability of highly specialized treatment options, etc. 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 and a reason for further investigation by the hospital.

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 is 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 annually estimates the models for expected mortality per diagnosis for the most recent three-year period. It calculates 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 data 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. Individual hospital reports, containing their HSMR and 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 mortality 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 value 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 are

registered uniformly, but the registration of whether an admission was acute or not, the main discharge diagnosis or 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 sufficiently 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 those patients 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 sufficiently adjusts for this phenomenon, since some essential information regarding severity or complexity of disease 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 registry with routinely collected hospital discharge data.

- 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 due to higher availability of external terminal care facilities in the neighbourhood. Also, patients may be referred from one hospital to another for further treatment. Obviously, all these situations that mostly are unrelated to quality of care also influence the outcome of the HSMR, as they influence the observed mortality numbers.

– Hospitals can compare their HSMR and SMRs with the national average value 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 peer group comparison allows a specialised hospital to compare its results with the average for similar hospitals. 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. Pouw *et al*. (2013) performed a retrospective analysis on Dutch hospital data linked to mortality data, and concluded that including early post-discharge mortality diminishes 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). Including all mortality within a 45-day period after admission was advised to reduce the influence of hospital discharge policies on the HSMR. In addition, a French study also recommended fixed post-admission periods of more than 30 days (Lamarche-Vadel et al., 2015).

However, including post-discharge mortality in the indicator will not reduce the effect of differences in admission policies for terminally ill patients. Some hospitals may admit more terminally ill patients to provide terminal palliative care than other hospitals and those admissions may distort HSMR outcomes. Palliative care in general 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 ICD-10 code Z51.5 does not distinguish between early and terminal 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-based indicators like the HSMR, there are also studies that suggest that mortality monitoring can be indicative of failings in quality of care. 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 a mortality alerting system might be valuable in highlighting poor quality of care.

2. Method changes

This chapter summarizes the changes in the HSMR method (HSMR 2020) compared to the method used last year (HSMR 2019). For previous changes see the respective methodological reports (CBS, 2011, …, 2020). Overall, the method has remained the same. Only a few changes related to selection of the data have been implemented, which are explained below.

Due to the COVID-19 pandemic, 2020 has been an extraordinary year. The pandemic has significantly affected hospital care and, especially in the first epidemic wave, specific expertise for treating COVID-19 was lacking. In addition, the COVID-19 admissions were rather different from regular admissions due to their mostly acute nature, their frequent need for intensive care and prolonged length of stay. Therefore, in agreement with the Dutch Healthcare Authority (NZa) and the Health and Youth Care Inspectorate (IGJ), it was decided to omit the 2020 admissions with COVID-19 as main diagnosis (ICD-10 codes U07.1 (COVID-19, virus identified (lab confirmed)) and U07.2 (COVID-19, virus not identified (clinically diagnosed))) from the HSMR model. Admissions with COVID-19 as a comorbidity only, were not excluded. The admissions with COVID-19 as main diagnosis were also excluded from the dataset that was used to evaluate data quality and case mix (see section 3.5).
Thus, the 2020 HSMR values are based on regular (non-COVID-19 related) care and the included admissions in 2020 have similar main diagnoses compared to earlier years. Due to downscaling of regular hospital care as a result of the COVID-19 pandemic, and to a smaller extent also due to the exclusion of the COVID-19 admissions, the number of admissions of 2020 included in the model, was on average 14% lower than the number of 2019 admissions. The reduction of the number of admissions of 2020 varied over the hospitals and over the months of admission.

Although admissions with COVID-19 as main diagnosis have been excluded from the HSMR model, CBS has performed a number of analyses to determine whether and to what extent the COVID-19 pandemic might have influenced the hospital care not related to COVID-19. The outcome of these analyses is presented in Chapter 5. In order to provide the hospitals with relevant information that might help them to better interpret their current HSMR outcome, two additional tables have been included in the hospital reports. These tables report the following outcomes by month of admission in 2020: the total numbers of admissions and hospital deaths, the numbers of admissions and hospital deaths with COVID-19 as the principal diagnosis, the numbers of admissions and deaths included in the HSMR model, the SMR, the average SMR of all hospitals and the fraction of admissions with COVID-19, both for the hospital and for all hospitals.

Starting from 2020, DHD has added an additional variable to the comorbidities dataset called ‘source’. This variable indicates the source of each registered comorbidity: whether it was coded or verified by a medical coding expert or derived otherwise. For the HSMR model, only those comorbidities were selected that had either been coded by a medical coding expert or that had been derived from the medical files and had been verified by a medical coding expert. All main diagnoses had been registered in this manner. Registered comorbidities that had not been coded or verified by a medical coding expert, were excluded from the dataset. In previous years the comorbidities dataset contained only those comorbidities that met these criteria.

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 are 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 (NZa), and it replaces the majority of the acute one-day inpatient admissions that had formerly been registered. It involves more mortality than day cases, and it is therefore relevant to include this case type 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 100 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.
For the year 2020 all admissions with COVID-19 as the principal diagnosis (ICD-10 codes U07.1 (COVID-19, virus identified (lab confirmed)) and U07.2 (COVID-19, virus not identified (clinically diagnosed))) were removed from the dataset (see Chapter 2).

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 allows the evaluation of 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:

[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*

- 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).
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 and thus the (H)SMRs are adjusted for these characteristics. 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 of 0 or 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 home 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 2017 the SES classification of 2016 was used and for 2018-2020 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/LBZ 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 2018-2020 the severity classification was based on the LMR/LBZ of 2012-2017, which consists of a mix of mostly ICD-10 but also 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-10 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: *2017, 2018, 2019, 2020*.
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.

The criteria for excluding a hospital from calculating HSMRs, based on the characteristics of the registered inpatient admissions and prolonged observations without overnight stay, were:

Insufficient participation in the LBZ

- Hospitals are excluded if they do not register all inpatient admissions and "prolonged observations, unplanned, without overnight stay" that meet the billing criteria of the Dutch Healthcare Authority (NZa) in the LBZ.

Data quality

Hospitals are excluded if*:*

- ≤30% of admissions are coded as acute.
- ≤1.5 secondary diagnoses are registered per admission, on average per hospital.[2]

Case mix

Hospitals are excluded if:

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

Admissions with COVID-19 as main diagnosis were excluded from the dataset that was used to calculate the outcomes of the data quality and case mix criteria.

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

[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.

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

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

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

It follows from the above formulae that:

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

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 one. As a result of collapsing the categories, the degrees of freedom can be smaller than the original number of categories minus one.

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

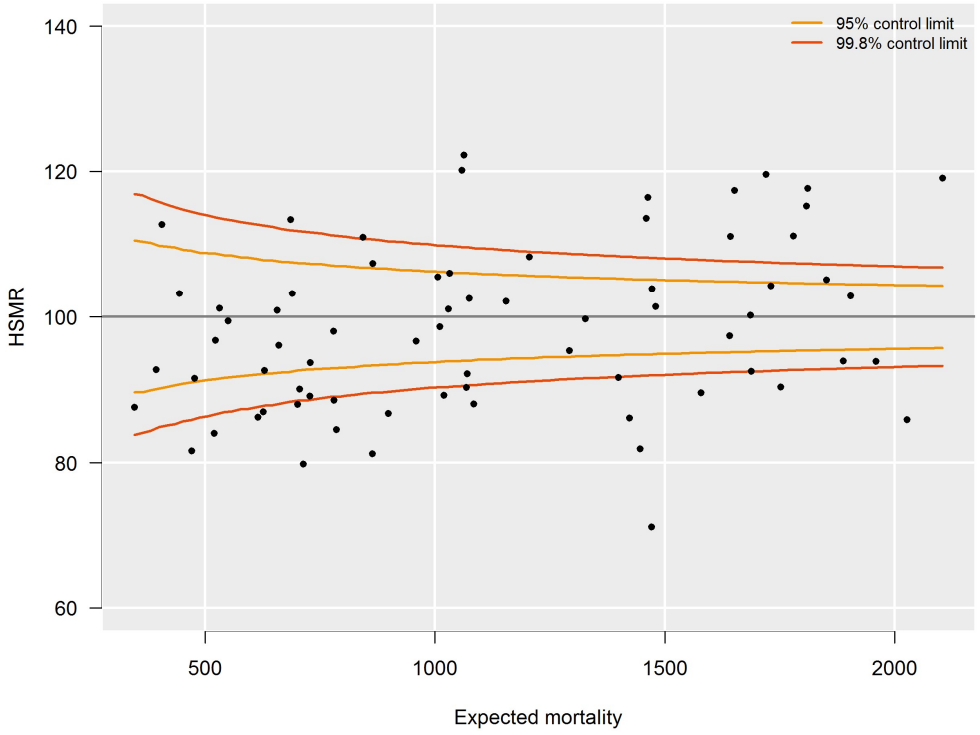
A confidence interval, i.e. an upper and lower confidence limit, is calculated for each SMR and HSMR. For the HSMR and most SMRs a confidence level of 95 percent is used, while for the SMRs of the 157 diagnosis groups a confidence level of 98 percent is used to reduce the number of undue statistically significant SMRs as a result of the large number of comparisons made when evaluating 157 diagnosis groups. 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 be 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 HSMR figures for the most recent 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 most recent 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 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 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 a 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 2020

This chapter presents and evaluates the model results. Summary outcomes 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 2020.xlsx", published together with this report.

4.1 Target population and data set

All hospitals that register complete records of inpatient admissions and prolonged observations without overnight stay in the LBZ are included in the HSMR model. In 2019 and 2020 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 2017-2020 all of the other hospitals had completely registered admission data in the LBZ. For the year 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 2020 (counting merged hospitals as one unit in previous years also), plus the closed hospitals that were included in the model in previous years, the total number of hospitals included in the HSMR model of 2017-2020 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

4.1.1 Admissions in HSMR model 2017-2020.

	2017	2018	2019	2020	total
Excluded admissions not meeting the NZa criteria*	10 600	87 723	138 310	123 889	360 522
Excluded admissions of foreigners	8 631	9 221	9 825	6 231	33 908
Excluded admissions due to COVID-19**				40 430	40 430
Total number of admissions included in model	1 718 535	1 647 563	1 636 522	1 413 747	6 416 367
Number of inpatient admissions	*1 606 419*	*1 541 992*	*1 523 148*	*1 306 395*	*5 977 954*
Number of observations	*112 116*	*105 571*	*113 374*	*107 352*	*438 413*
Number of deaths included in model	32 803	33 417	32 647	29 151	128 018
Crude mortality (in admissions in model)	1,9%	2,0%	2,0%	2,1%	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).*
***Admissions with COVID-19 as the principal diagnosis (ICD-10 codes U07.1 (COVID-19, virus identified (lab confirmed)) and U07.2 (COVID-19, virus not identified (clinically diagnosed))).*

admissions of foreigners were excluded. For the year 2020, admissions with COVID-19 as the principal diagnosis were additionally excluded. Due to that and due to the overall impact of the

COVID-19 pandemic on regular hospital care, the number of admissions included in 2020 was on average 14% lower compared to that of 2019. As a result, the total number of admissions in the 2020 model (6 416 367) was 5.3% lower than that in the 2019 model (6 777 534). This decrease was higher than the 2.8% reduction of admissions between the 2019 (6 777 534) and the 2018 model (6 974 721).
The crude mortality of the non-COVID-19 admissions included in the HSMR model stabilizes around 2.0% in the period 2017-2020. The COVID-19 admissions in 2020 (not included in the model) had a much higher in-hospital mortality rate (overall 15.5%). In the first COVID-19-wave of March-May 2020 the mortality rate of the COVID-19 admissions was 18.7%, decreasing to 10.0% in the summer period and increasing again to 13.9% during October-December 2020 in the second COVID-19-wave.

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 (2018-2020) 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 2020. The three other hospitals had closed down during or before 2018. Of the 75 hospitals that had registered complete data in 2020, 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 the data of three of these hospitals 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 2020.
For these 71 hospitals the data of 2019 and 2018 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.
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, 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 for group 2 (Congestive heart failure). Comorbidity 15 is only rarely registered as a comorbidity; most diagnosis groups had fewer than 50 admissions with HIV comorbidity. In none of the models comorbidity 15 was statistically significant. The number of times month of admission is significant varies over the years (CBS, 2018, 2019): it increased from 27 in 2017 to 43 in 2018, but in 2019 it decreased to 37 and to 35 in 2020. 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 2017-2020 model. Compared to the HSMR 2019 model, the largest changes were

observed for the covariates comorbidity 4 (Cerebrovascular disease, no longer significant in 9 models) and comorbidity 10 (Diabetes, no longer significant in 9 models). For the other covariates the changes are smaller. The total number of significant covariates decreased from 1 705 in 2019 to 1 666 in 2020. This decrease is somewhat larger than in 2018-2019, which is probably caused by the fact that the COVID-19 pandemic led to a decrease in the number of admissions in the HSMR model.

4.3.1 Statistical significance of the covariates for the 157 logistic regressions (summary), HSMR 2020 model.

Covariate	No. of significant results	Covariate	No. of significant results
Age	139	Comorbidity 1	57
Comorbidity 2	129	Comorbidity 17	48
Urgency	124	Sex	47
Severity main diagnosis	120	Month of admission	35
Comorbidity 13	110	Comorbidity 10	34
Comorbidity 16	105	Comorbidity 12	34
Comorbidity 3	100	Comorbidity 11	24
Comorbidity 9	93	Year of discharge	22
Source of admission	92	Comorbidity 7	21
Comorbidity 6	89	SES	18
Comorbidity 14	74	Comorbidity 8	12
Comorbidity 4	73	Comorbidity 15	0
Comorbidity 5	66		

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 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 2019 model (CBS, 2020), the order of the covariates is almost identical. Note that the values of the Walds statistics themselves cannot be compared directly as these values depend on the number of admissions used in the models. This also explains the smaller values in the model of 2020 compared to the 2019 model.

When comparing the outcomes of the past six models (HSMR 2015 up to HSMR 2020) 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 models of 2019 and 2020 the Wald statistics of year of discharge has stabilized. The impact of the comorbidities 3 (peripheral vascular disease), 5 (dementia) and 12 (hemiplegia or paraplegia) has increased considerably (>40%) over the past six HSMR models, although the impact of comorbidities 3 and 5 showed no further increase in the HSMR 2020 model. This could be caused by an increased effect of these comorbidities (e.g. the likelihood of dying in hospital when having these conditions as comorbidity 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). On the

other hand, the impact of comorbidity 1 (myocardial infarction) has decreased by approximately 40% over the past six models.

4.3.2 Wald chi-square statistics for the 157 logistic regressions, HSMR 2020 model.

Covariate	Sum of Wald statistics	Sum of df	Covariate	Sum of Wald statistics	Sum of df
Severity main diagnosis	40 491	394	Comorbidity 4	1 382	126
Age	31 200	1 992	Comorbidity 5	1 285	120
Urgency	16 984	155	Sex	926	148
Comorbidity 2	9 949	145	SES	833	692
Comorbidity 16	4 889	139	Comorbidity 12	813	102
Comorbidity 13	4 031	151	Comorbidity 1	774	148
Source of admission	3 228	286	Year of discharge	740	468
Comorbidity 3	2 760	145	Comorbidity 10	491	151
Comorbidity 6	2 464	152	Comorbidity 11	326	117
Comorbidity 9	1 902	131	Comorbidity 7	277	123
Comorbidity 14	1 497	144	Comorbidity 8	132	31
Month of admission	1 495	778	Comorbidity 15	8	9
Comorbidity 17	1 456	60			

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 2020, 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 2020 by inclusion/deletion of covariates.

Covariate	Average shift in HSMR	Covariate	Average shift in HSMR
Comorbidity *	5.83	Source of admission	1.14
Age	4.24	SES	0.77
Severity main diagnosis	2.93	Month of admission	0.15
Urgency	1.97	Sex	0.11

**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 the previous model. Apart from the C-statistic of "Cancer of testis and other male genital organs" that increased from 0.89 to 0.94, all other changes are smaller than 0.05 with most of them below 0.02. For 77 diagnosis groups the C-statistic did not change compared to last year. Therefore, even though the number of admissions used in the HSMR models has decreased because of the COVID-19 pandemic, the predictive power of the models is the same as in previous years.

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 2020 model.

Diag. group no.	Description of diagnosis group	Number of admissions	Number of deaths	C-statistic
1	Tuberculosis	1 674	39	0.88
2	Septicemia (except in labor)	15 740	4 105	0.73
3	Bacterial infection; unspecified site	9 247	489	0.81
4	Mycoses	2 166	171	0.84
5	HIV infection	816	38	0.83
6	Hepatitis, viral and other infections	26 512	245	0.94
7	Cancer of head and neck	15 218	249	0.89
8	Cancer of esophagus	11 306	574	0.81
9	Cancer of stomach	12 770	476	0.82
10	Cancer of colon	47 234	1 192	0.84
11	Cancer of rectum and anus	21 205	423	0.86
12	Cancer of liver and intrahepatic bile duct	7 665	428	0.81
13	Cancer of pancreas	18 826	881	0.82
14	Cancer of other GI organs; peritoneum	8 561	392	0.80
15	Cancer of bronchus; lung	64 380	4 388	0.83
16	Cancer; other respiratory and intrathoracic	3 022	131	0.84
17	Cancer of bone and connective tissue	8 203	92	0.93
18	Melanomas of skin and other non-epithelial cancer of skin	7 446	107	0.94
19	Cancer of breast	43 087	428	0.96
20	Cancer of uterus	8 916	120	0.92
21	Cancer of cervix and other female genital organs	11 989	95	0.92
22	Cancer of ovary	9 234	287	0.84
23	Cancer of prostate	26 069	356	0.93
24	Cancer of testis and other male genital organs	6 640	11	0.94
25	Cancer of bladder	54 905	495	0.93

26	Cancer of kidney, renal pelvis and other urinary organs	15 903	289	0.88
27	Cancer of brain and nervous system	12 081	279	0.78
28	Cancer of thyroid	5 928	48	0.97
29	Hodgkin`s disease	2 109	35	0.91
30	Non-Hodgkin`s lymphoma	22 386	970	0.82
31	Leukemias	22 485	1230	0.81
32	Multiple myeloma	10 999	480	0.81
33	Cancer; other and unspec. primary; maintenance chemotherapy and radioth.	5 604	132	0.92
34	Secondary malignancies	83 101	4 284	0.77
35	Malignant neoplasm without specification of site	4 008	375	0.84
36	Neoplasms of unspecified nature or uncertain behavior	12 915	229	0.89
37	Other and unspecified benign neoplasm	71 294	101	0.89
38	Thyroid and other endocrine disorders	24 491	207	0.92
39	Diabetes mellitus without complication	15 433	119	0.89
40	Diabetes mellitus with complications	24 680	524	0.86
41	Nutritional deficiencies and other nutritional, endocrine, and metabolic disorders	58 158	439	0.95
42	Fluid and electrolyte disorders	36 225	870	0.84
43	Cystic fibrosis	2 370	12	0.93
44	Immunity and coagulation disorders, hemorrhagic disorders	11 232	190	0.87
45	Deficiency and other anemia	47 087	446	0.81
46	Diseases of white blood cells	8 823	202	0.78
47	Mental, affective, anxiety, somatoform, dissociative, and personality disorders	23 488	69	0.90
48	Senility and organic mental disorders	10 506	483	0.72
49	Schizophrenia, mental retardation, preadult disorders and other mental cond.	7 189	17	0.87
50	Other psychoses	3 291	30	0.84
51	Meningitis, encephalitis, and other central nervous system infections	10 346	541	0.89
52	Parkinson`s disease	6 272	102	0.86
53	Multiple sclerosis and other degenerative nervous system conditions	13 635	273	0.91
54	Paralysis and late effects of cerebrovascular disease	4 206	56	0.87
55	Epilepsy and convulsions	45 425	567	0.90
56	Coma, stupor, and brain damage	2 524	262	0.90
57	Headache and other disorders of the sense organs	70 603	42	0.94
58	Other nervous system disorders	77 985	324	0.95
59	Heart valve disorders	38 267	928	0.77
60	Peri-, endo-, myocarditis, and cardiomyopathy	22 582	678	0.87
61	Essential hypertension, hypertension with compl., and secondary hypertension	14 047	110	0.95
62	Acute myocardial infarction	135 548	3 588	0.85
63	Coronary atherosclerosis and other heart disease	128 509	858	0.85
64	Nonspecific chest pain	168 555	48	0.91
65	Pulmonary heart disease	32 129	1 042	0.80
66	Other and ill-defined heart disease	2 006	128	0.91

67	Conduction disorders (heart disease)	25 219	320	0.89
68	Cardiac dysrhythmias	194 364	791	0.90
69	Cardiac arrest and ventricular fibrillation	15 125	5 568	0.75
70	Congestive heart failure, nonhypertensive	122 982	9 833	0.68
71	Acute cerebrovascular disease	150 079	12 844	0.81
72	Transient cerebral ischemia, and other cerebrovascular disease	47 489	375	0.89
73	Peripheral and visceral atherosclerosis	44 270	1 918	0.91
74	Aortic and other artery aneurysms	27 667	2 482	0.89
75	Aortic and arterial embolism or thrombosis	13 200	438	0.88
76	Other circulatory disease	31 090	577	0.87
77	Phlebitis, varicose veins, and hemorrhoids	12 740	143	0.88
78	Pneumonia	132 272	10 737	0.76
79	Influenza	23 136	1 245	0.80
80	Tonsillitis and upper respiratory infections	69 104	132	0.94
81	Acute bronchitis	23 657	85	0.95
82	Chronic obstructive pulmonary disease and bronchiectasis	124 443	6 852	0.70
83	Asthma	28 814	108	0.91
84	Aspiration pneumonitis; food/vomitus	8 506	1 736	0.65
85	Pleurisy; pneumothorax; pulmonary collapse	24 449	594	0.85
86	Respiratory failure; insufficiency; arrest	6 681	2 009	0.75
87	Lung disease due to external agents	1 838	164	0.79
88	Other lower respiratory disease	26 334	910	0.88
89	Other upper respiratory disease	66 073	369	0.91
90	Intestinal infection	51 141	574	0.89
91	Disorders of mouth, teeth, and jaw	21 650	51	0.98
92	Esophageal disorders	13 946	109	0.92
93	Gastroduodenal ulcer	4 997	229	0.92
94	Gastritis, duodenitis, and other disorders of stomach and duodenum	7 822	90	0.89
95	Appendicitis and other appendiceal conditions	68 674	64	0.98
96	Peritonitis and intestinal abscess	4 918	334	0.82
97	Abdominal hernia	48 291	440	0.92
98	Regional enteritis and ulcerative colitis	18 383	59	0.96
99	Intestinal obstruction without hernia	33 395	1 567	0.83
100	Diverticulosis and diverticulitis	36 721	492	0.92
101	Anal and rectal conditions	23 842	42	0.94
102	Biliary tract disease	128 335	978	0.91
103	Liver disease; alcohol-related	7 244	886	0.72
104	Other liver diseases	17 872	990	0.83
105	Pancreatic disorders (not diabetes)	34 890	719	0.83
106	Gastrointestinal hemorrhage	37 894	1 011	0.81
107	Noninfectious gastroenteritis	12 931	202	0.84
108	Other gastrointestinal disorders	40 637	736	0.95
109	Nephritis; nephrosis; renal sclerosis	14 772	103	0.91
110	Acute and unspecified renal failure	16 785	1 029	0.78
111	Chronic kidney disease	14 823	459	0.89
112	Urinary tract infections	99 646	2 534	0.78
113	Calculus and other diseases of urinary tract	86 268	221	0.91

114	Genitourinary symptoms and ill-defined conditions	27 836	98	0.88
115	Hyperplasia of prostate and other male genital disorders	43 380	40	0.91
116	Non-neoplastic breast conditions	16 468	2	0.99
117	Prolapse and other female genital disorders	66 856	40	0.99
118	Complications of pregnancy, childbirth, and the puerperium; liveborn	584 951	15	0.86
119	Skin and subcutaneous tissue infections	56 486	683	0.91
120	Other skin disorders, chronic ulcer of skin	19 387	232	0.93
121	Infective arthritis and osteomyelitis	13 870	262	0.89
122	Osteoarthritis, rheumatoid arthritis, and other musculoskeletal deformities	243 385	191	0.92
123	Other non-traumatic joint disorders	13 579	37	0.94
124	Spondylosis, back problems, and osteoporosis	90 582	182	0.98
125	Pathological fracture	5 694	79	0.80
126	Other connective tissue disease	40 900	264	0.97
127	Cardiac and circulatory congenital anomalies	9 399	188	0.88
128	Noncardiac congenital anomalies	28 583	221	0.95
129	Short gestation; low birth weight; and fetal growth retardation	69 998	472	0.90
130	Intrauterine hypoxia, perinatal asphyxia, and jaundice	59 162	234	0.94
131	Other perinatal conditions	216 221	244	0.95
132	Joint disorders and dislocations; trauma-related; sprains and strains	28 934	34	0.98
133	Fracture of neck of femur (hip)	83 882	2 658	0.81
134	Skull and face fractures, spinal cord injury	12 469	231	0.90
135	Fracture of upper limb	46 037	143	0.95
136	Fracture of lower limb	51 593	289	0.94
137	Other fractures	45 528	999	0.87
138	Intracranial injury	40 152	2 473	0.80
139	Crushing injury or internal injury	22 135	429	0.92
140	Open wounds of head; neck; and trunk	6 510	53	0.89
141	Open wounds of extremities	5 691	38	0.94
142	Complication of device, implant or graft	99 395	1 310	0.88
143	Complications of surgical procedures or medical care	103 412	832	0.86
144	Superficial injury; contusion	61 072	473	0.93
145	Burns	4 034	96	0.93
146	Poisoning by psychotropic agents, drugs, or other medications	38 098	344	0.88
147	Other injuries and conditions due to external causes	12 827	644	0.89
148	Syncope	47 984	135	0.87
149	Fever of other and unknown origin	23 688	124	0.84
150	Lymphadenitis and gangrene	4 719	28	0.96
151	Shock	1 215	456	0.73
152	Nausea and vomiting	13 542	80	0.85
153	Abdominal pain	48 138	133	0.95
154	Malaise and fatigue	10 512	160	0.84
155	Allergic reactions	12 495	31	0.96
156	Rehabilitation and other aftercare, medical examination/evaluation/screening	94 581	217	0.87
157	Residual codes; unclassified	68 322	156	0.97

4.5 Regression coefficients

The file “coefficients HSMR 2020.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 2020.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).

5. Effect of the COVID-19 pandemic on the HSMR

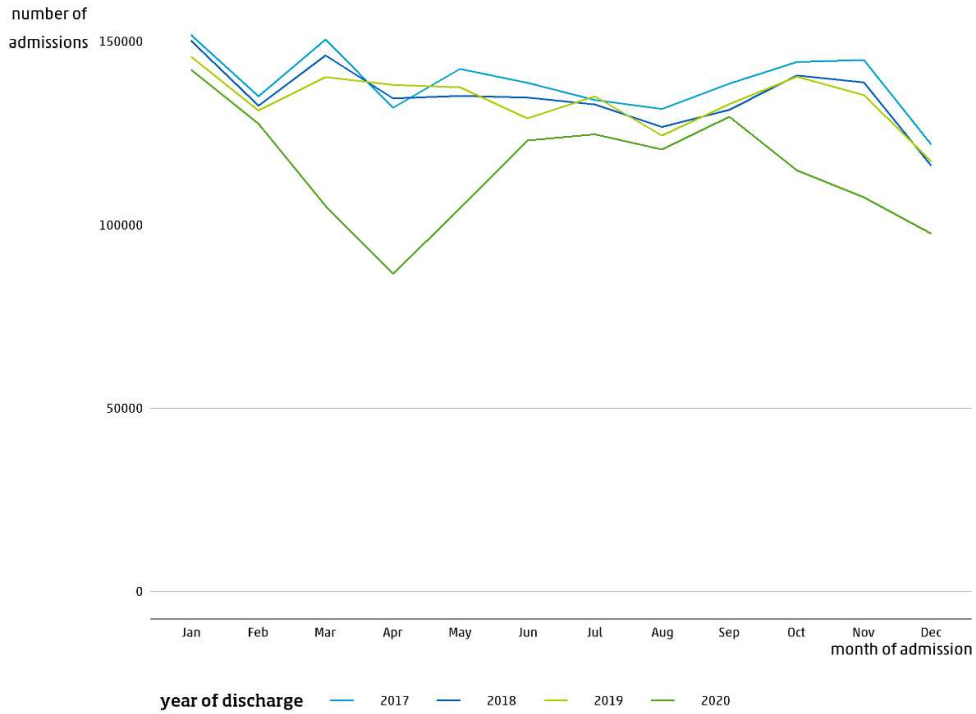
Because of the expected heterogeneities in care for COVID-19 admissions, it was decided to not include admissions with COVID-19 as main diagnosis in the HSMR model and the calculated HSMRs and SMRs (see chapter 2). This was done because it is unlikely that the HSMR model can sufficiently correct for differences in patient populations between hospitals for these admissions. For example, the pandemic hit different regions at different times and during the pandemic hospitals were still developing protocols for these patients. These differences are difficult to capture in the HSMR model. Therefore, over 40 000 admissions with main diagnosis COVID-19 are excluded from the HSMR. However, regular hospital care was also affected by the pandemic. For example, elective admissions were postponed and patients were admitted in other hospitals than they would otherwise have been. If these effects are not captured in the measured properties of the admissions, the HSMRs and SMRs could be (indirectly) affected by the pandemic. In order to investigate these effects, this chapter contains an explorative analysis of the effect of the COVID-19 waves on the (H)SMRs of regular hospital care. We investigated whether several aspects of the (H)SMR outcomes were significantly different in 2020 when compared to previous years.

There are two ways in which the HSMR can be influenced by the pandemic. The pandemic can have caused a shift in the types of patients that were admitted (e.g. less elective care). This shift will probably be unequal across hospitals. When the HSMR model is not able to correct for these shifts in the types of patients admitted this will cause shifts in the HSMRs not related to changes in the quality of care. At the same time the actual care for non-COVID-19 patients can also have been influenced by the pandemic also causing shifts in the HSMR. The analyses in this chapter cannot distinguish between these two effects. The best we can do with the available data is to check if we can detect these shifts in the HSMRs (and SMRs). If we cannot detect these shifts, it is likely that the model is able to correct for changes in the patient population and that quality of care for non-COVID-19 patients was not strongly affected. If we do detect changes in the (H)SMRs any of the previously mentioned effects could have caused this, which means care should be taken when interpreting the measured HSMRs and SMRs.

5.1 Number of admissions and deaths

The number of hospital admissions selected for the HSMR model (i.e. inpatient admissions and prolonged observations without overnight stay) is low in 2020 compared to previous years. According to table 4.1.1 the number of admissions in the model decreased with 14% in 2020 compared to 2019. This is not only due to the exclusion of the COVID-19 admissions, but is for a larger part also due to downscaling of regular hospital care because of the pandemic. Figure 5.1.1 shows the number of non-COVID-19 admissions per month of admission for 2020 and for earlier years. The number of admissions is typically a little lower during the summer months. In 2020 however, the number of admissions is clearly lower during the first COVID-19 wave from March to May and during the second wave from October onwards. The number of admissions had dropped with 32.1% in April compared to February, while during the summer months the number of admissions was more comparable to that of earlier years, although it was still somewhat lower. Another drop in admissions occurred during the second wave from October onwards. Note that the number of admissions in the last months of the year (particularly December) is artificially lower in figure 5.1.1 for all years, as the admissions with an admission date in the end of the year and a discharge date in the next year are not shown.

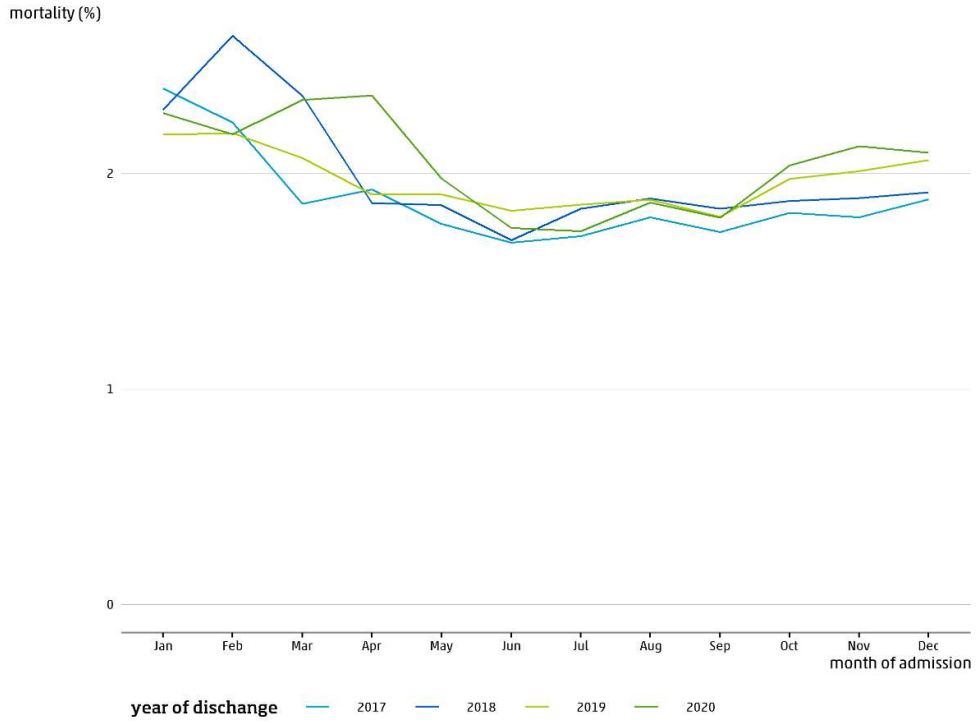
5.1.1 Number of hospital admissions by month of admission and year of discharge.[a]



[a]*Admissions that had started in the year prior to the year of discharge are not included. Therefore, the displayed numbers of admissions in the last months of the year do not correctly reflect the total number of admissions in those months.*

While the number of admissions is clearly lower during the COVID-19 waves, the crude mortality rate of regular hospital care only shows a modest increase during the two COVID-19 waves. Figure 5.1.2 shows that the in-hospital mortality rate is higher in March and April 2020, is still slightly higher in May, reaches normal levels during the summer months and is increased again during the second pandemic wave compared to the same months in previous years. In February 2018 the mortality rate was also higher, probably caused by the more severe influenza epidemic in that year, which probably led to more hospital admissions and mortality (included in the HSMR model). Overall, it seems that the pandemic has led to a slightly higher crude mortality rate of the non-COVID-19 admissions during the COVID-19 waves. However, if this increase is caused by giving priority to admitting the more severely ill patients and if this selection effect is captured by the model, the HSMRs and SMRs need not be affected. This will be investigated in the next section.

5.1.2 Crude in-hospital mortality rate by month of admission and year of discharge.[a]



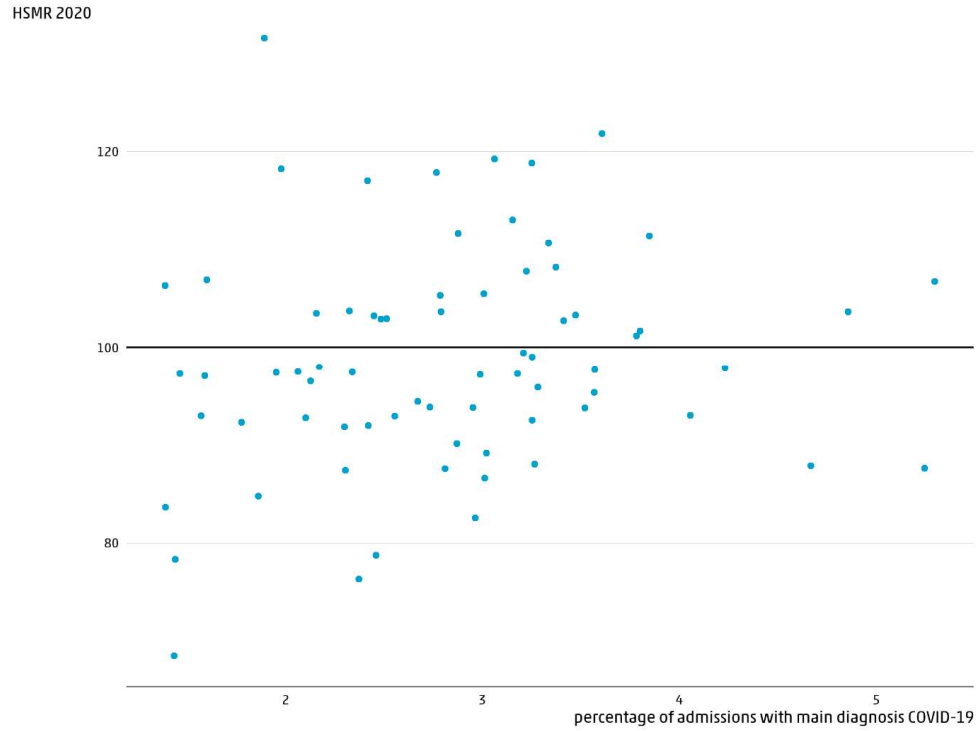
[a] *Admissions that had started in the year prior to the year of discharge are not included.*

5.2 HSMR in relation to the COVID-19 admissions

In this paragraph we will explore whether there are relationships between the HSMRs, based on the non-COVID-19 hospital admissions, and the pressure on hospitals caused by the COVID-19 pandemic in 2020. If the pandemic affects the HSMR, we would expect that this depends on the degree to which hospitals are affected by the pandemic. We will use the fraction of admissions with main diagnosis COVID-19 in the hospital as a measure for how severely the pandemic affected care in that hospital. Note that care can also be affected in other ways not visible in the fraction of admissions with main diagnosis COVID-19.

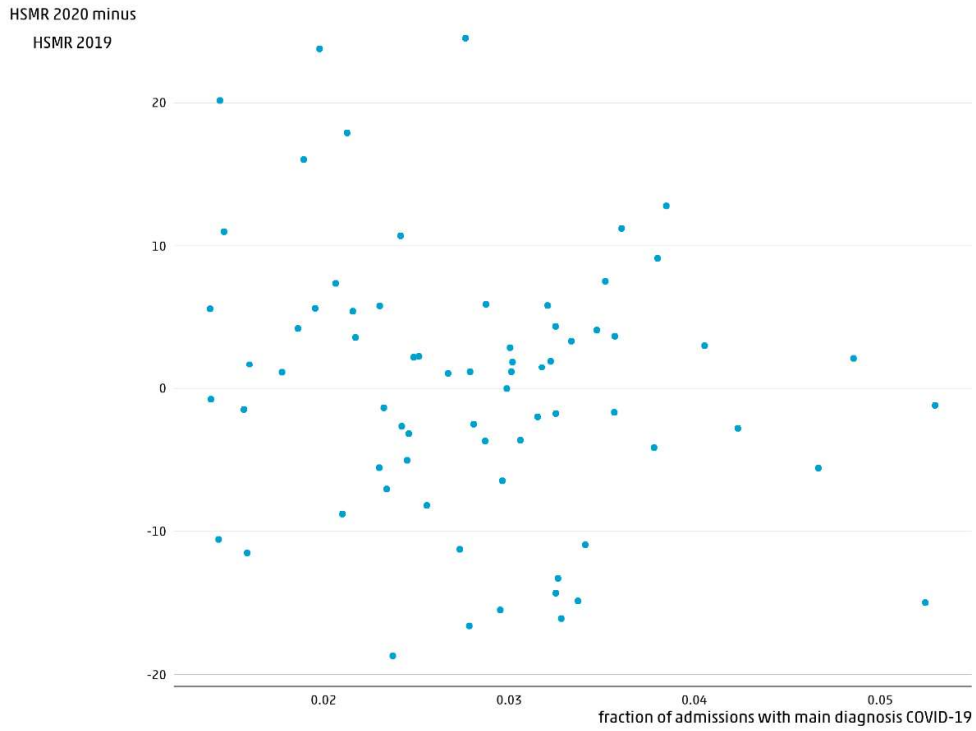
In figure 5.2.1 the hospitals are plotted with their HSMR 2020 of the regular hospital care versus their fraction of COVID-19 admissions. It appears that there is no statistically significant relationship (r=-0.15; p-value=0.21) between the two outcomes. We also analysed the relationship between the HSMR 2020 and the fraction of COVID-19 admissions for three types of hospitals (university hospitals, general hospitals with some specializations, and other general hospitals) and by size of the hospitals (number of admissions). This was tested by linear regression of the fraction of COVID-19 admissions on the HSMR by adding type of hospital or size as an interaction in the model. No statistically significant relationships were found here either (data not shown).

5.2.1 HSMR 2020 per hospital versus the percentage of admissions with main diagnosis COVID-19.



However, also in previous years (before the pandemic) the HSMRs show quite a large inter-hospital variation. It could be that this regular variation in the HSMRs dominates the effect of the pandemic. However, hospitals that score high or low on their HSMR in one year are in general likely to score high or low again the next year. Therefore, any change in the HSMR caused by the pandemic, can be more clearly seen by comparing HSMR values of 2020 to that of 2019 for each hospital. In that way we take into account the correlation between the yearly HSMRs. If the pandemic affected the HSMRs, we would expect systemic intra-hospital changes in the HSMRs that are related to the level of the pressure on the hospitals caused by the pandemic. Figure 5.2.2 therefore shows the relation between the difference between the HSMR in 2020 and 2019 for each individual hospital and the fraction of COVID-19 admissions in 2020. Again, there is no clear relation between the fraction of patients with COVID-19 and the change in the HSMR (r=-0.19, p-value=0.11). We also analysed the relationship between the HSMR 2020 and HSMR 2019 difference and the fraction of COVID-19 admissions by type and size of hospital. Again, no relationships were found (data not shown).
In the previous analyses we have not found an effect of the pandemic on the HSMRs. This is also confirmed by table 5.2.3 that shows the number of significantly high or low HSMRs and the variation in the HSMRs. These are also similar to those of previous years.

5.2.2 Difference between the HSMR 2020 and HSMR 2019 versus the fraction of admissions with main diagnosis COVID-19.



5.2.3 Number of HSMRs in 2018, 2019 and 2020 that are significantly different from 100 (α=0.05) and the variation in HSMRs per year.

Year of discharge	Number of HSMRs that are significantly lower than 100	Number of HSMRs that are significantly higher than 100	Standard deviation of the HSMRs
2018	14	12	11.84
2019	12	10	11.29
2020	11	10	11.43

5.3 Regional differences

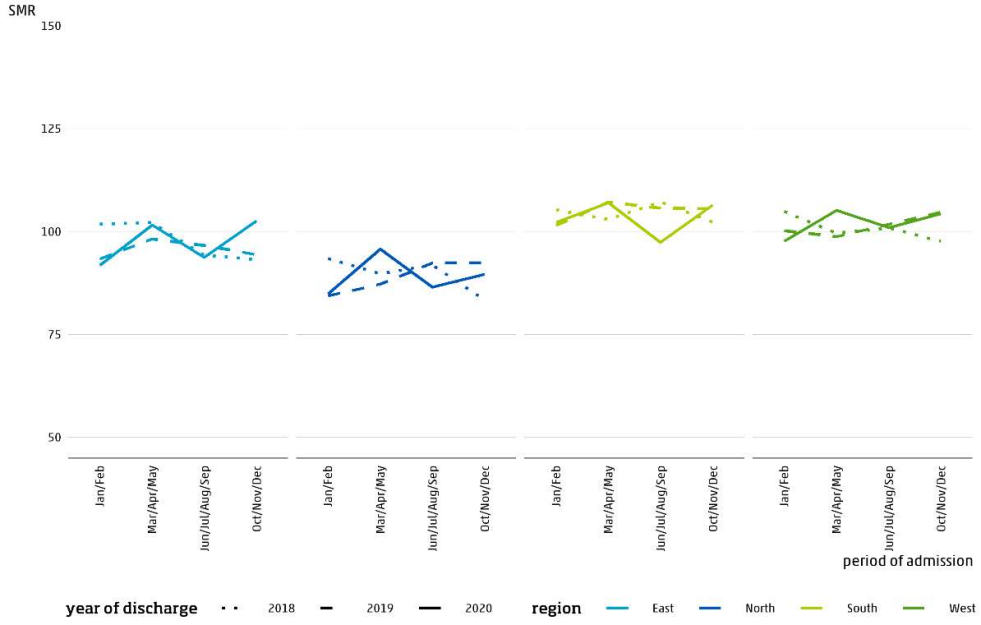
The pandemic hit different regions in the Netherlands at different times. The first wave (March-May) mainly hit the south of the Netherlands, while the second wave (October-December) hit the west harder. Table 5.3.1 shows the HSMR 2020 per region (HSMR of all hospitals in the specific region combined). For comparison the regional HSMRs of 2018 and 2019 are also shown. The number of hospitals and the number of admissions differs between regions. There are also differences in HSMR between regions, but these differences are relatively stable over the years. The south of the Netherlands has had the highest mean fraction of COVID-19 admissions in 2020, but the difference in HSMR 2020 with the west is small. The HSMR 2020 per region does not seem to be affected by the COVID-19 admissions, as the HSMRs are comparable

to those of previous years. To zoom more into the different waves of the pandemic, figure 5.3.2 shows the SMR per region per period. No differences can be seen between regions in the pattern of the SMRs per period in 2020. Although in 2020 the SMRs overall seem higher during both waves of the pandemic and lower during the summer months, the SMR values were not significantly different from the SMRs in the same periods in previous years (see next section).

5.3.1 HSMR of 2018, 2019 and 2020 per region of the Netherlands, together with the number of hospitals and admissions per region and the percentage of COVID-19 admissions in 2020.

Region	HSMR 2018	HSMR 2019	HSMR 2020	Number of hospitals	Number of admissions in 2020	Percentage of COVID-19 admissions
North (Groningen/ Drenthe/ Friesland)	89.9	89.1	89.0	9	149 316	1.51
East (Overijssel/ Gelderland/ Flevoland)	97.8	95.8	97.2	15	301 133	2.64
West (Utrecht/ Noord-Holland/ Zuid-Holland/ Zeeland)	100.9	101.6	102.1	32	655 421	2.91
South (Noord-Brabant/ Limburg)	104.5	105.2	102.7	15	294 235	3.38

5.3.2 SMRs per region, year of discharge and period of admission.[a]

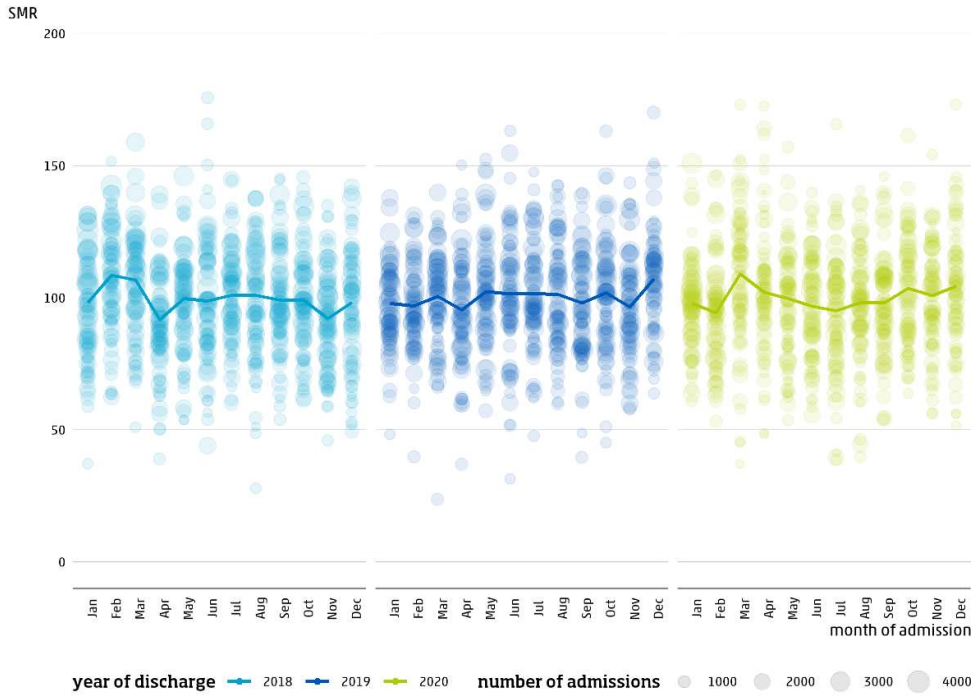


[a] The months of admission are grouped according to the 2020 COVID-19 waves (first wave March-May and second wave October-December). (Expected) mortality of admissions that started in the year prior to the year of discharge year is not included in the SMRs.

5.4 Effect of pandemic on monthly SMRs

The previous sections showed that there is no clear effect of the pandemic on the yearly HSMRs. This section zooms in further and investigates the monthly SMRs of the hospitals. Figure 5.4.1 shows the SMRs per month of admission for three consecutive years for each individual hospital together with the average SMR per month of admission. The increased average SMR in the first months of 2018 is probably related to the more severe influenza epidemic that year. Compared to the average SMRs of the same months in the previous years, the level of the mean SMRs during the two COVID-19 waves is not significantly different. The patterns in the crude mortality rate as shown in figure 5.1.2 and the overall SMR are somewhat similar; both time series show the COVID-19 waves and the influenza epidemic of 2018. However, while the crude mortality rate peaks in April 2020, the average monthly SMR has a peak in March and decreases in April. The SMR in March 2020 is not significantly different compared to previous years. The SMR in April 2020, however, is significantly different compared to the SMR in April 2018 and 2019, this might be due to the relatively low SMR in April in previous years.
The variation in the monthly SMRs is only slightly increased in March and April 2020. The overall standard deviation of the monthly SMR is 21.1 for 2020 which is higher than that of 2019 which was 20.0, but not significantly higher than that of 2018 which was 21.0. This corresponds to the results from table 5.2.3. So overall, the outcomes of 2020 are not extremely different compared to those of previous years when looking at the monthly SMRs.

5.4.1 Monthly SMRs (dots) and the overall SMR (line) per month, 2018-2020.*



** A dot represents the outcome of an individual hospital. The size of the dots is proportional to the number of admissions. (Expected) mortality of admissions that started in the year prior to the year of discharge year is not included in the SMRs.*

Although the variation in the monthly SMRs in 2020 is not very different from that in previous years, SMRs could be increased during one or more months of the COVID-19 waves for specific hospitals. Table 5.4.2 shows that the percentage of monthly SMRs that are significantly different from 100 is somewhat higher in the first half of 2020, and relatively low during the second pandemic wave. This is also the case when compared to the same periods in 2018 and 2019 (except for the deviant first months of 2018 mentioned earlier). The monthly SMRs did not differ significantly from 100 during the COVID-19 waves for most of the hospitals. Only for one or two hospitals there was an indication that their SMRs of some months during the COVID-19 waves were higher than expected, when taking the variation in previous years into account.

5.4.2 Percentage of monthly SMRs that are significantly different from 100 (α=0.05) per period, 2018-2020.

Period	2018	2019	2020
January/ February	16.20	7.04	9.86
March/ April/ May	8.45	7.51	9.39
June/ July/ August/ September	5.99	5.28	6.69
October/ November/ December	6.57	8.45	4.69

5.5 Effect of pandemic on diagnoses and type of admissions

The results of the previous analyses do not indicate a clear or large effect of the pandemic on the HSMRs. Although the overall (H)SMRs are not affected, it is possible that the SMRs of certain diagnoses are affected while the SMRs of most other diagnoses are not. In order to investigate this, the average SMR is calculated for each diagnosis group and for clusters of diagnosis groups for each of the two pandemic waves and compared to the expected average value of 100. As elective care was scaled down and acute care could have been disturbed during the pandemic waves, it is also investigated if there are differences in the SMRs of elective and acute admissions during the different pandemic periods. SMRs that are significantly different from 100 might indicate that the model is not able to correct appropriately for certain classes of covariates during the pandemic waves, or it might indicate that the quality of care was affected.

The SMR is calculated for each of the 157 diagnosis groups. Therefore, we performed 157 tests for each period to test the hypothesis that the SMR of a diagnosis group is not different from its expected value, which leads to an increased risk of a type I error called the multiple testing problem. To reduce the chance to mistakenly reject the null-hypothesis that an SMR is equal to 100 a Bonferroni correction is applied: the significance level is adjusted according to the number of tests, with a default significance level of 0.1. The Bonferroni correction is a little conservative, as it increases the risk of a type II error.

We performed two types of tests for each diagnosis group:

1. The SMR of a diagnosis group in a certain COVID-19 wave is equal to 100;
2. The SMR of a diagnosis group in a certain month of 2020 is equal to 100.

The first type of test gives a general impression of remarkably high and low SMRs during the pandemic waves and the second type of test zooms into the SMRs per month. Note that the tests are not strictly independent, since the yearly SMR per diagnosis group is by definition

equal to 100. The Bonferroni correction equals 157 (the number of diagnosis groups) times 2 (the number of COVID-19 waves) or times 12 (the number of months).
We also applied the Bonferrroni correction for the tests of clusters of diagnosis groups (the 17 clusters mentioned in paragraph 3.3) and the tests of elective and acute admissions.

The results of the tests with Bonferroni correction for the 157 diagnosis groups showed that none of the SMRs differed significantly from 100 during the months of 2020 and the two pandemic waves. We are also interested in SMRs that are high, even though they are not significantly different from 100 when the Bonferroni correction is applied. When we omit the Bonferroni correction there is only one significant result: table 5.5.1 shows that the SMR of diagnosis group 'other fractures' (diagnosis group no. 137) is significantly high (α=0.05) in March 2020, but the lower-bound is only just above 100, and the SMRs of the pandemic wave periods are not significant. We compared the monthly SMRs of 2020 of this diagnosis group with those of 2018 and 2019, which indeed shows a peak in March 2020, but there is also a smaller peak in August 2019. So the peak in March 2020 is not exceptional and may be a coincidence as the Bonferroni correction did not show significant results. We also calculated the SMRs per hospital, month and diagnosis group, to explore if the increased SMR of other fractures is due to admissions in a specific hospital. None of the monthly SMRs per hospital was significantly different from 100. It can therefore be concluded that no clear deviances can be seen in the SMRs of the 157 diagnosis groups that could indicate an effect of the pandemic.

5.5.1 Significant SMRs (α=0.05) per diagnosis group and period, 2020 (without Bonferroni correction).

Diagnosis group	Month of admission	Crude mortality	Number of admissions	SMR	Lower-bound SMR	Upper-bound SMR	p-value
Other fractures	March	39	694	184.81	100.17	309.02	0.0004

However, it may be that possible effects become visible on a more aggregated level only. Therefore we also tested for the 17 clusters of diagnosis groups whether the SMR is equal to its expected value during the pandemic waves and months of 2020. With Bonferroni correction this gave one significant result: the SMR of cluster 'diseases of the respiratory system' is significantly different from 100 during the second COVID-19 wave (see table 5.5.2). Although the SMRs per individual month were not significantly different from 100, figure 5.5.3 indeed shows a slightly increased SMR during the last three months of the year. However, these SMRs are not much higher than in February and March 2018 (when there was a severe influenza epidemic), where the SMR of March 2018 was significantly different from 100. Note that the SMR in April 2020 is also higher than in previous years, whereas the SMR in March 2020 is very similar to that of 2019. We conclude that the SMR of the diseases of the respiratory system might be influenced by the disturbances during the second pandemic wave, although the lower bound of the SMR is only slightly above 100. It is not known in what way the pandemic has possibly influenced this SMR. The number of admissions for (non-COVID-19) respiratory diseases showed a larger decrease in 2020 than the admissions for other diagnosis clusters. Perhaps the characteristics of these patients were somewhat different compared to other years and these differences were not captured sufficiently in the HSMR model. Or maybe the pandemic caused in particular problems for the care on lung departments, e.g. staff shortage.

There is no indication that these patients more often had COVID-19 as a comorbidity which also could have explained the measured effect. However, it should be noted that the SMR of diseases of the respiratory system is only modestly increased (SMR=110.52) during the second pandemic wave, so the possible effect of the pandemic does not seem large.

5.5.2 Significant SMRs per cluster of diagnosis groups and period, 2020.

Diagnosis cluster	Period of admission	Crude mortality	Number of admissions	SMR	Lower-bound SMR	Upper-bound SMR	p-value
Diseases of the respiratory system	October-December	924	18408	110.52	100.02	121.77	0.0028

5.5.3 Monthly SMRs of diseases of the respiratory system, 2018-2020.

** (Expected) mortality of admissions that started in the year prior to the year of discharge year is not included in the SMRs*

Again we repeated the tests without the Bonferroni correction, since we are also interested in other clusters with relatively high SMRs. The SMR of cluster 'injury and poisoning' is high during the month March as described in table 5.5.4. This cluster consists of nine diagnosis groups, and one of the diagnosis groups is 'other fractures', for which a statistically significant result (without Bonferroni correction) was described earlier (see table 5.5.1). Other diagnosis groups of this cluster are not significantly different from 100 in March, but still relatively high compared to the other months of 2020. The time series of SMRs in 2018, 2019 and 2020 in figure 5.5.5 shows that there is no peak visible in March 2018 and March 2019. Since the SMR differs from 100 in only one month in 2020, at the start of the COVID-19 pandemic, this could possibly be related to the pandemic, but there could also be other causes for the increased SMR. The results should be interpreted with caution as the Bonferroni correction did not show significant results for this cluster.

5.5.4 Significant SMRs (α=0.05) per cluster of diagnosis groups and period, 2020 (without Bonferroni correction).

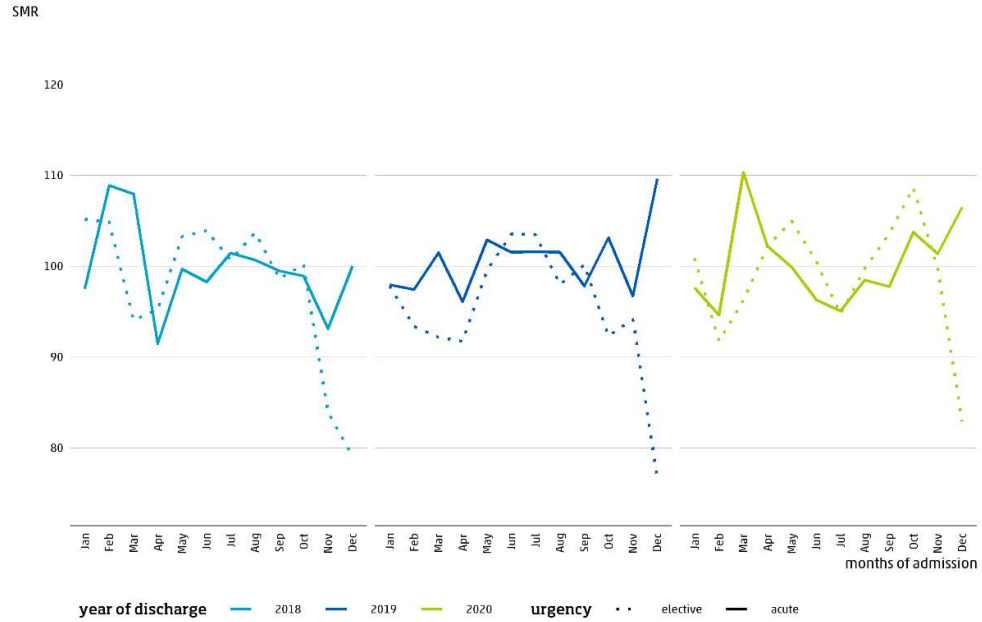
Diagnosis cluster	Month of admission	Crude mortality	Number of admissions	SMR	Lower-bound SMR	Upper-bound SMR	p-value
Injury and poisoning	March	250	10968	125.41	103.13	150.86	0.0005

5.5.5 Monthly SMRs of Injury and poisoning, 2018-2020.*

** (Expected) mortality of admissions that started in the year prior to the year of discharge year is not included in the SMRs*

One of the effects of the pandemic was that for the non-COVID-19 care hospitals gave priority to acute care and postponed part of the elective care. Therefore, it is not unlikely that elective cases have been affected differently than acute cases. We calculated the SMRs for acute and elective admissions per COVID-19 wave period (Mar-May and Oct-Dec) and per month in 2020 and tested if these SMRs are equal to 100 during these periods. The confidence intervals are rather small compared to the diagnosis groups, since the groups of the acute and elective admissions are larger. The SMR of acute admissions is significantly different from 100 during the first (SMR 104.32; p-value 0.0010) and second COVID-19 wave (SMR 103.75; p-value 0.0040). These SMR values are however only just above 100. The monthly SMR of acute admissions is significant in March 2020 only (SMR 110.32; p-value 0.0000). For elective admissions there were no significant results. The time series of SMRs in 2018, 2019 and 2020 are shown in figure 5.5.6. The figure shows that also in previous years there is some variation in the monthly SMRs for acute and elective admissions. The SMR for acute admissions in March 2020 is not much higher than in February and March 2018, which SMRs were also significantly higher than 100. Note that the deviant results in December (in all years) are due to the fact that the mortality of admissions that ended in the next year is not included.

5.5.6 Monthly SMRs for acute and elective admissions, 2018-2020.*



** (Expected) mortality of admissions that started in the year prior to the year of discharge year is not included in the SMRs*

In this section we looked at the SMRs for different months of admission and for the pandemic wave periods in 2020 for diagnosis groups, clusters of diagnosis groups and acute and elective admissions. All in all the results are not very clear. Most outcomes are not statistically significant, and also in previous years there is variation in the levels of the SMRs. There are some cases where the SMRs seem to be higher than expected during the COVID-19 waves: the SMR for diseases of the respiratory system is modestly increased in the second pandemic wave of October-December 2020, the SMR for acute admissions is increased mainly in March 2020, and the SMR related to injuries seems high in March 2020. These may possibly be effects of the pandemic, but even if so, the effects appear to be small.

6. Conclusions

Sections 4.4 and 4.5 evaluate the quality of the HSMR model of 2017-2020. No significant differences were found compared to the models of previous years. The importance of the variables in the model has remained largely the same and the predictive power of the model has remained the same. Therefore, it seems that the present model, in which the COVID-19 admissions in 2020 are excluded, is not significantly affected by the COVID-19 pandemic. However, the model is estimated using four years of data. Therefore, it is possible that it is not affected by the pandemic, while the HSMRs and SMRs for 2020 are. The four-year model might not work as well for some of the admissions in 2020 if the changes in casemix (e.g. less elective care) are not sufficiently corrected for by the model. Therefore, in chapter 5 we investigated if there are indications that the HSMRs and SMRs are affected.

The main assumption in these analyses is that, if there is an effect of the pandemic on regular care, this will mainly be during the two main COVID-19 waves and this effect will be stronger for hospitals more affected by COVID-19. The degree to which a hospital is affected is measured using the fraction of admissions with main diagnosis COVID-19 in that hospital in 2020. The relation between the fraction COVID-19 admissions and the HSMRs was analysed, including interactions with region and type and size of hospital. Small effects were found, but these were similar to variations seen in previous years. It was also analysed if specific SMRs for diagnosis groups and for elective and acute admissions were significantly different during the months of the pandemic waves and compared to the same periods in previous years. For the diagnosis cluster ‘diseases of the respiratory system’ a modest increase in SMRs was found during the second wave of the pandemic (Oct-Dec 2020) and for acute admissions an increase in SMR was found mainly in March 2020, as was probably the case for admissions related to injuries. Although the effects are small, care has to be taken when comparing results of these groups to previous years as for these groups the model may be unable to correct completely for changes in the patient population caused by the pandemic and/or the actual care for non-COVID-19 patients may have been affected by the pandemic. Overall all effects found were small and therefore we conclude from this explorative analysis that the HSMR is not strongly affected by the COVID-19 pandemic in general and that results are in general comparable to previous years.

As the pandemic still holds on in 2021, we will have to investigate how the COVID-19 admissions will be handled in the HSMR models for 2021 and later years.

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Appendix. Statistical significance of covariates, HSMR 2020 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	0	1	-	-	-	-	-	0	-	-	0	0	-	-	1	-	-	-	-	0	0	0	0
2	1	1	1	0	0	1	1	1	1	1	0	1	1	0	0	0	1	1	-	1	1	0	1	0	1
3	1	1	1	0	1	1	0	1	0	1	0	-	0	0	1	1	1	1	-	1	1	0	0	0	0
4	1	0	1	1	0	1	0	-	-	0	0	-	1	0	-	-	1	0	-	1	-	0	0	0	1
5	0	0	0	1	-	-	-	-	-	0	-	-	1	-	-	-	-	1	0	-	-	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	1	0	1	1	0	0	-	1	0	-	-	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	0
9	0	0	1	1	0	1	1	1	1	0	1	1	1	0	0	-	1	0	-	1	-	0	0	0	0
10	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	0	1	1	-	1	1	0	0	0	1
11	0	0	1	1	0	1	1	0	0	1	0	-	1	1	0	0	1	0	-	1	-	0	0	0	0
12	0	0	1	1	0	1	0	-	-	0	0	-	0	0	0	-	1	0	-	1	1	0	1	0	0
13	0	1	1	1	0	1	1	1	0	1	0	1	1	0	1	-	1	1	-	1	1	0	1	0	1
14	1	0	1	1	0	1	0	0	0	1	0	0	1	0	0	-	1	0	-	1	-	0	0	0	0
15	1	1	1	1	1	1	1	1	0	1	1	-	1	0	0	1	1	1	-	1	1	0	1	0	1

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

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

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

94	1	0	1	1	1	1	0	0	1	0	0	0	0	0	0	-	1	0	-	0	0	0	0	0	0
95	-	0	1	0	0	1	1	0	0	1	0	-	1	1	0	-	1	1	-	0	-	0	0	0	1
96	1	0	1	1	0	1	1	-	-	0	0	-	1	0	0	-	1	1	-	1	1	0	0	0	1
97	1	1	1	1	0	1	1	0	0	1	0	0	1	1	0	0	1	0	-	0	1	0	1	0	0
98	1	0	1	1	1	1	1	0	-	0	0	-	0	0	-	-	1	1	-	0	0	0	0	0	0
99	1	0	1	1	1	1	1	1	1	1	0	1	1	0	0	1	1	1	-	1	-	1	1	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	0	0	0	1	1	-	0	0	0	-	0	0	-	1	-	0	0	0	1
102	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	0	1	1	-	1	1	0	0	0	1
103	1	0	0	1	0	1	1	0	-	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	0	0	1	0	-	1	1	-	1	1	0	0	0	1
105	1	0	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	1	-	0	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	0	1
107	1	0	1	1	0	1	0	0	0	1	0	-	0	0	0	1	1	1	-	1	0	0	0	0	0
108	1	0	1	1	0	1	1	0	1	1	1	0	1	0	0	0	1	0	-	1	0	0	0	0	1
109	1	0	1	1	1	1	1	0	0	0	0	-	1	0	0	0	0	1	-	1	-	0	0	0	0
110	1	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	-	1	1	0	1	0	1
111	1	1	1	1	1	1	1	0	1	1	0	-	1	0	1	0	1	1	-	0	-	1	1	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	0	0	1	1	0	1	0	0	1	1	0	-	1	0	0	0	0	0	-	1	-	0	0	0	0
115	1	-	1	1	0	0	1	-	0	0	-	-	0	0	1	-	1	0	-	1	-	1	0	0	0
116	-	-	0	-	-	-	-	-	-	0	-	-	-	-	-	-	-	0	-	0	-	0	0	0	-
117	1	-	1	1	0	1	0	-	1	1	1	-	1	1	-	0	0	0	-	0	-	0	0	1	0
118	1	-	1	0	-	-	-	-	-	-	-	-	0	-	-	-	1	-	-	-	-	0	0	0	0
119	1	1	1	0	1	1	1	1	0	1	1	-	1	1	1	0	1	1	-	1	1	0	1	0	1

120	1	0	1	1	0	1	1	0	0	0	0	-	1	0	0	0	1	0	-	1	-	0	0	0	1
121	1	1	1	1	0	1	0	1	0	1	0	-	1	0	0	0	1	1	-	0	-	0	0	0	0
122	1	0	1	1	1	1	1	1	0	1	0	-	1	0	0	1	1	1	-	1	-	0	0	0	1
123	0	0	1	1	0	1	0	0	0	0	0	-	-	0	0	-	1	1	-	0	-	0	0	0	0
124	1	0	1	1	0	1	1	1	0	1	1	-	1	1	0	1	1	0	-	1	-	0	0	0	1
125	0	0	1	1	0	1	1	0	0	0	0	-	1	0	0	0	0	0	-	1	-	0	0	0	0
126	1	0	1	1	0	1	1	0	0	1	0	-	1	0	0	-	1	1	-	1	-	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	-	-	0	0	-	-	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	0	0	1	1	-	0	0	-	-	-	0	-	1	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	1	1	0
134	1	0	1	1	0	0	1	0	1	1	0	-	-	0	-	1	0	0	-	-	-	0	0	1	0
135	1	1	1	1	0	1	1	1	0	1	0	-	1	1	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	1	0	1
137	1	1	1	1	1	1	1	1	1	1	0	-	1	1	0	1	1	1	-	1	-	1	1	1	1
138	1	1	1	1	1	1	1	1	1	1	0	-	1	0	1	0	1	1	-	1	-	0	0	0	0
139	1	1	1	1	1	1	1	1	1	1	0	-	1	0	0	1	1	0	-	1	-	0	1	0	1
140	0	0	1	-	0	1	0	0	0	0	-	-	-	0	-	-	1	0	-	-	-	0	0	0	0
141	1	0	1	1	1	0	0	-	1	0	1	-	-	0	-	-	1	-	-	-	-	0	0	0	0
142	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	0	0	0	1
143	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	0	1	1	-	1	1	0	0	1	1
144	1	1	1	0	0	1	1	1	1	1	0	-	1	1	0	0	1	1	-	1	-	1	1	0	0
145	1	0	1	1	0	-	1	-	-	0	-	-	-	0	0	-	0	-	-	-	-	0	0	0	0

146	1	0	1	0	0	1	1	1	0	1	0	-	0	0	0	0	1	0	-	0	1	0	1	0	1
147	1	0	1	1	0	1	1	1	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	-	1	0	0	0	1	1	-	1	-	0	1	0	0
149	-	0	1	0	1	1	1	0	0	0	0	-	0	0	0	0	0	1	-	1	-	0	0	0	0
150	1	1	1	1	1	0	0	-	-	0	-	-	0	0	0	-	1	0	-	0	-	0	0	0	0
151	1	1	1	0	1	0	1	-	-	0	-	-	0	0	-	-	0	0	-	0	-	0	1	0	0
152	-	0	1	0	0	1	1	0	0	0	0	-	0	0	0	0	0	0	-	1	-	0	0	0	0
153	1	0	1	1	0	1	1	0	1	1	0	-	1	0	0	0	1	0	-	1	0	0	0	0	0
154	-	0	1	0	0	1	1	0	0	0	0	-	1	0	1	1	0	0	-	1	-	0	0	0	1
155	1	0	1	0	0	1	0	-	-	0	0	-	1	0	0	-	1	1	-	0	-	0	0	0	0
156	-	0	1	1	0	1	1	1	0	1	0	-	1	0	0	1	1	1	-	0	1	0	0	0	1
157	1	0	1	1	0	1	0	0	1	0	0	-	1	0	0	0	1	1	-	1	1	0	0	0	1
total	120	47	139	124	57	129	100	73	66	89	21	12	93	34	24	34	110	74	0	105	48	18	35	22	92

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 symbols

Empty cell	Figure not applicable
.	Figure is unknown, insufficiently reliable or confidential
*	Provisional figure
**	Revised provisional figure
–	(between two numbers) inclusive
0 (0.0)	Less than half of unit concerned
2020–2021	2020 to 2021 inclusive
2020/2021	Average for 2020 up to and including 2021
2020/'21	Crop year, financial year, school year, etc., beginning in 2020 and ending in 2021
2018/'19–2020/'21	Crop year, etc., 2018/'19 to 2020/'21 inclusive

Because of rounding, some totals may not correspond to the sum of the separate cells.
Revised figures are not marked as such.

Colophon

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Statistics Netherlands
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www.cbs.nl

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Information
Telephone +31 88 570 70 70
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