

## Appendix

### Binary logistic regression method

To construct a model based on fiscal year 2004 data (n = 2 135 964) that estimated the expected number of cases in which palliation was the most responsible discharge diagnosis, potential variables were first examined in univariate analysis to select candidate predictors. Variables examined included age, gender, transfer status, medical or surgical case, length of stay, elective or urgent category, Charlson score, number of interventions, number of diagnoses and diagnostic types. Significant variables were then entered as covariates using the backward Wald procedure in SPSS. Variables were first entered as continuous if possible, and then examined as categorical. Nagelkerke R<sup>2</sup> and Hosmer-Lemeshow statistics were used to evaluate model fit. Nearing the construction of the final model, covariance matrices for correlations of estimates were performed to check for collinearity. A collinear relationship between the constant and age was found; however, the standard error of the beta coefficient for age was very small and eliminating age as a predictor worsened the model fit, so the variable was kept. The final model was:

Predictor	$\beta$ -coefficient (SE)	p value
Constant	-9.180 (0.044)	<0.001
metastatic cancer as any discharge diagnosis	3.595 (0.017)	<0.001
length of stay 22 days or more	1.058 (0.022)	<0.001
age in years	0.026 (0.001)	<0.001
no interventions*	1.530 (0.026)	<0.001
medical case**	1.077 (0.037)	<0.001

\*defined as having no discharge Canadian Classification of Health Interventions codes

\*\*defined in the same manner described by CIHI <sup>1</sup>.

Area under the receiver-operator curve (AUROC) analysis was then done to assess for model discrimination, with a value of 0.909.

To reconstruct a binary logistic regression model for HSMR that included palliative cases, we entered all variables identically categorized as per CIHI, but included code Z51.5 as a diagnostic group. We kept all variables regardless of significance, collinearity or fit to keep the model as close to the original HSMR as possible. The AUROC for this model was 0.852. Next, we did the same procedure but excluded the main diagnosis as a variable. The AUROC for this model was 0.732. Coefficients are available on request.

#### Estimating a coefficient for palliative cases based on the literature

With a literature search we identified two studies reporting the natural history of people admitted to Canadian inpatient palliative units. The characteristics of the study populations when mortality reached 50% were extracted in the framework of variables used to calculate the CIHI HSMR, and a literature-based scenario was built to reflect this as shown below:

Reference	mean age	% female	length of stay	admission category	comorbidity	transferred from
Jenkins et al. <sup>21</sup>	75	55	21 days	elective	100% malignancy, presume metastatic	46% from acute care hospital
Napolskikh	76	52	19 days	elective	92%	61% from

et al. <sup>22</sup>					malignancy, presume metastatic	acute care hospital
literature-based scenario	75	female	16-21 day group	elective	Charlson score >2	from acute care hospital

To back-calculate a literature-based coefficient for cases in which palliation is the main diagnosis, we used the equations and coefficients provided by CIHI<sup>1</sup> as below:

$$\text{probability of death} = e^S / (1 + e^S)$$

$$S = \text{intercept} + (\text{age in year} * \text{age coefficient}) + (\text{sex coefficient}) + (\text{length of stay coefficient}) + (\text{admission category coefficient}) + (\text{diagnosis group coefficient}) + (\text{comorbidity coefficient}) + (\text{transfer coefficient})$$

and made the appropriate substitutions to arrive at a “diagnosis group coefficient” for palliative cases.