Appendix 1 (as supplied by the authors)

This document contains detailed methodology and technical details associated with the calculations performed in the paper.

Prepared on August 9, 2020

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Time series forecasting methodology

Four time series forecasting models were used to estimate the surgical backlog size by region and by surgery type. Each of the models were trained on historical weekly data from January 1, 2017 to October 12, 2019 and validated on data from October 13, 2019 to March 8, 2020. For each of the models, the root mean squared error (RMSE) was calculated using the observed and predicted data from the validation period. The model with the lowest RMSE was selected to forecast the volumes into the future.

Model performance metrics along with the selected model by region and surgery type can be found in "Model performance statistics" section of this document.

Here are **summary descriptions of each of the models**. A full treatment along with sample R code can be found here [Forecasting: Principles and Practice, Rob J Hyndman and George Athanasopoulos Monash University, Australia] https://otexts.com/fpp2/.

1. Seasonal naïve model
    a. Each forecast is set to be equal to the last observed value from the same season of the year. In this case, the seasonal period considered was a weekly basis. For example, if the value of week 35 is 20 surgeries in the previous year, then the forecast for week 35 in the current year being forecasted is 20.
    b. This model is used for region/surgery type forecasts where weekly volumes are lower than 50. In particular, this model was used for transplants and cardiac to forecast expected volumes, and in select situations for other disease sites where volumes were low. See the "Model performance statistics" section of this document for details on which surgery types/regions used the seasonal naïve model.
2. Seasonal and trend decomposition using loess (STL)
    a. STL is a filtering procedure decomposing the time series into trend, seasonal, and remainder (error) components. The trend component indicates the general direction of the data (increasing, decreasing or flat). The seasonality component accounts for regular and predictive patterns that recur in a fixed time interval (in this case, weeks). The remainder component captures the random or unpredictable fluctuations in the data. The algorithm performs a sequence of applications of the loess smoother to estimate the seasonal and trend components. Loess regression is a nonparametric technique that uses local weighted regression to fit a smooth curve through points in a sequence.
    b. To forecast the decomposed time series, we forecast the seasonal component, and the seasonally adjusted component, separately. The forecast for the seasonal part uses the last year of the estimated seasonal component from the decomposition. To forecast the seasonally adjusted component, any non-seasonal forecasting method may be used. We evaluated state space (ETS) and autoregressive moving average (ARIMA) models for the seasonally adjusted component and selected the model with the best performance according to the RMSE.
3. Dynamic harmonic regression with Fourier terms for seasonality
    a. This method is a linear regression model where the seasonal pattern is modelled using trigonometric functions ("Fourier terms") and the short-term time series dynamics are handled by an autoregressive moving average (ARMA) error. Seasonality is assumed to be

periodic and is approximated by the sums of *k* pairs of trigonometric terms (sine and cosine).
   b. The total number of Fourier terms (k) for the weekly seasonal period have been chosen to minimize the Akaike information criterion corrected for the sample size (AICc). The order of the ARIMA model is also selected by minimizing the AICc.
   c. The main disadvantage with this method is that seasonality is assumed to be fixed over the forecasting period.

4. TBATS state space models
   a. This model uses a combination of Fourier terms with an exponential smoothing state space model and a Box-Cox transformation. It allows for the seasonality to change slowly over time and thus can capture changes in seasonality which won't be captured by the dynamic harmonic regression.

Since the forecast errors were normally distributed, the 95% prediction intervals were calculated as the mean forecast ± 1.96*(estimate of the standard deviation of the h-step forecast distribution) [https://otexts.com/fpp2/prediction-intervals.html].

Model performance statistics

Time series forecasting model performance

SN	Seasonal Naïve Model
STL	Seasonal and Trend Decomposition using loess
DARIMA	Dynamic ARIMA model
TBATS	TBATS state space model
RMSE	Root Mean Squared Error

SurgeryType	OH_region	Priority	Selected Model	RMSE (SN)	RMSE (STL)	RMSE (DARIMA)	RMSE (TBATS)
Benign	Central	P2+P3	STL without Box-Cox transformation	166.70	52.73	100.86	103.02
Benign	Central	P4	STL with Box-Cox transformation	549.54	219.83	388.21	450.04
Paeds	Central	P2+P3	STL with Box-Cox transformation	12.87	8.54	10.73	10.38
Paeds	Central	P4	STL without Box-Cox transformation	64.56	31.48	44.67	45.33
Benign	East	P2+P3	STL with Box-Cox transformation	186.91	92.40	124.58	136.49
Benign	East	P4	STL without Box-Cox transformation	646.47	282.56	391.57	377.91
Paeds	East	P2+P3	STL with Box-Cox transformation	37.14	21.73	25.82	27.25
Paeds	East	P4	STL with Box-Cox transformation	54.90	27.50	36.73	41.70
Benign	North	P2+P3	STL without Box-Cox transformation	39.10	24.43	27.23	29.84
Benign	North	P4	TBATS(1, {0,0}, -, {<52.18,16>})	174.14	86.80	122.58	78.85
Paeds	North	P2+P3	Seasonal Naïve	11.16	NA	NA	NA
Paeds	North	P4	STL without Box-Cox transformation	21.50	11.52	15.19	15.63
Benign	Toronto	P2+P3	STL without Box-Cox transformation	77.68	30.12	45.79	52.68
Benign	Toronto	P4	STL without Box-Cox transformation	318.09	91.38	207.88	270.70
Paeds	Toronto	P2+P3	STL without Box-Cox transformation	28.32	16.58	19.63	23.63
Paeds	Toronto	P4	STL without Box-Cox transformation	39.14	21.07	30.92	28.55
Benign	West	P2+P3	TBATS(1, {1,0}, -, {<52.18,16>})	173.27	89.94	101.21	79.83
Benign	West	P4	STL without Box-Cox transformation	774.43	335.54	449.45	551.46
Paeds	West	P2+P3	TBATS(1, {2,0}, 0.812, {<52.18,8>})	32.39	20.45	18.37	17.97
Paeds	West	P4	STL with Box-Cox transformation	69.59	46.12	49.84	50.02
ONC	Central	P2+P3	STL without Box-Cox transformation	39.67	17.04	28.22	26.36
ONC	Central	P4	STL without Box-Cox transformation	29.36	14.94	23.88	28.29
VASC	Central	P2+P3	STL with Box-Cox transformation	12.86	6.83	9.72	10.53
VASC	Central	P4	Seasonal Naïve	10.89	NA	NA	NA
ONC	East	P2+P3	STL without Box-Cox transformation	47.48	23.69	35.56	37.69
ONC	East	P4	STL without Box-Cox transformation	42.25	17.72	28.00	28.31
VASC	East	P2+P3	STL without Box-Cox transformation	12.66	7.87	8.24	9.40
VASC	East	P4	Seasonal Naïve	8.89	NA	NA	NA
ONC	North	P2+P3	STL without Box-Cox transformation	19.58	13.52	14.05	14.95
ONC	North	P4	Seasonal Naïve	7.03	NA	NA	NA
VASC	North	P2+P3	Seasonal Naïve	5.70	NA	NA	NA
VASC	North	P4	Seasonal Naïve	1.65	NA	NA	NA
ONC	Toronto	P2+P3	STL with Box-Cox transformation	39.51	15.78	25.97	31.35
ONC	Toronto	P4	STL with Box-Cox transformation	44.82	15.56	27.44	29.73
VASC	Toronto	P2+P3	Seasonal Naïve	5.76	NA	NA	NA
VASC	Toronto	P4	Seasonal Naïve	4.36	NA	NA	NA
ONC	West	P2+P3	STL without Box-Cox transformation	57.21	32.79	37.51	39.21
ONC	West	P4	STL without Box-Cox transformation	39.54	22.03	32.09	42.98
VASC	West	P2+P3	STL with Box-Cox transformation	13.66	8.89	10.71	10.72
VASC	West	P4	TBATS(1, {0,0}, -, {<52.18,6>})	11.26	11.04	11.08	9.45

For transplant and cardiac, due to small volumes, only a seasonal naïve model was used to forecast the expected surgical volumes by region during the pandemic period; as such, the RMSE is not reported for these forecasts.

Little’s law from queuing theory

Little’s law comes from the discipline of queuing theory and states that the average number of customers L in a queuing system is equal to the average arrival rate λ multiplied by the average time W that a customer spends in the system.

Expressed algebraically,

$$L = \lambda W$$

The relationship is independent of the arrival process distribution, the service distribution, or the service order. It has also been proven to hold for finite time processes under non-stationary conditions (i.e., a process whose joint probability distributions changes with time).

In the case of surgical backlog processing, we have an estimated value for the size of the queue (surgical backlog) and an estimated service rate (OR throughput). The average time spent waiting for service (or the average time until L surgeries are processed) can be obtained via Little’s law:

$$W = \frac{L}{\lambda}$$

or

$$Clearance\ Time = \frac{Backlog\ Size}{OR\ Throughput}$$

Reference:

John D. C. Little, 2011. "OR FORUM---Little's Law as Viewed on Its 50th Anniversary," Operations Research, INFORMS, vol. 59(3), pages 536-549, June.

https://www.informs.org/content/download/255808/2414681/file/little_paper.pdf

Probabilistic sensitivity analysis

Probabilistic sensitivity analysis (PSA) involves modelling the input parameters as probability distributions as opposed to point estimates. A Monte Carlo simulation is conducted (in the case of this paper, 1000 trials) that randomly selects a value from each input distribution to perform the calculation. The result is 1000 possible outcomes, after which summary statistics (such as mean and 95% confidence intervals) can be calculated. In this case, the 95% confidence interval is calculated by the 2.5% percentile and the 97.5% percentile of the 1000 possible outcomes.

For example, the clearance time calculation can be simplified and expressed as follows:

$$Clearance\ Time = \frac{Backlog\ Size}{OR\ Throughput}$$

In a deterministic analysis, a point estimate of the backlog size (45,000 patients) would be divided by a point estimate of the OR throughput (700 patients per week). This would yield a clearance time of 64.3 weeks. While this is a simple calculation, it assumes that there is no uncertainty with the backlog size estimation or the OR throughput calculation.

In reality, suppose there is some variation around the backlog size estimation (assume a normal distribution with a mean of 45,000 and standard deviation of 5,000) and the OR throughput (assume a normal distribution with a mean of 700 and standard deviation of 100). Running a PSA on these input distributions would yield a mean clearance time of 65.6 (95% CI: 45.1 to 93.9) weeks. This allows for a more accurate estimation of the mean clearance time (even more so if the input distributions are heavily skewed) as well as the ability to include 95% confidence intervals around the estimate to illustrate the uncertainty.

For this paper, the input parameters with uncertainty were:

1) Backlog size
2) OR time
3) Ward length of stay (LOS)
4) ICU LOS
5) Turnover time
6) % of ORs available for surge capacity.

The first 5 input variables were parameterized using historical distribution data by surgery type and by region. The turnover time was sampled from the pandemic period (June 2020) to reflect the increase in turnover time required as a result of additional infection control protocols in the OR. The turnover time was estimated for each region across all surgery types. Because of the uncertainty around the parameter, the % of ORs available for surge was assumed to be normal, with a mean of 50% and a standard deviation of 10%.

This means that each trial of the PSA had 11 surgery types by 5 regions by 4 input variables – 220 unique variables for each trial. Including regional turnover time distribution estimates and % of ORs available estimates, there are 226 variables for each trial or 226,000 inputs for the PSA.

Data source descriptions

Six administrative data sources were used to parameterize this model. We provide descriptions on the four Ontario specific datasets here:

1) Wait Times Information System (WTIS)
    a. The Access to Care (ATC) program at Ontario Health measures, manages, and reports on 58 surgical wait time data elements for over 9.4 million procedures since 2006, from over 3,200 surgeons at 92 facilities (122 sites) across the province (~650,000 procedures per year)
    b. A comprehensive picture of performance at the provincial, regional, hospital, and surgeon-level is available in near real-time
    c. In near real time, the Wait Time Information System (WTIS) supports the management of surgical wait lists by tracking patients waiting for a specific procedure based on their defined priority level
    d. As much as possible, wait time reporting guidance is framed to best reflect the wait time from a patient's perspective
    e. Data is entered into the WTIS via an online web browser through manual submission, or electronically using HL7 interface messaging, or a combination of these two methods
    f. Data is usually provided by surgeons' offices, although some facilities coordinate waitlist entry submission through OR booking resources
    g. Waitlist entries for patients are opened within 48 hours of the decision to treat (DTT), and closed within 48 hours of the procedure date
    h. Linkages to Ontario's provincial patient registry, the eHealth Ontario Provincial Client Registry (PCR), reduces duplication and increases quality through patient-level matching
2) Surgery Efficiency Target Program (SETP)
    a. ATC facilitates data capture and leads the management and reporting of 20 key surgical efficiency metrics from over 850 operating rooms from 75 hospitals (108 sites)
    b. The Surgical Efficiency Targets Program (SETP) uses data about operating room performance to monitor processes, and to identify and analyze areas where performance opportunities and issues may exist in perioperative patient care
    c. This program helps to optimize surgical capacity in Ontario, increase access to surgical services and maintain high-quality patient care
    d. SETP monitors 20 key performance indicators (KPIs) in five categories: Case Time Accuracy, Case Time Effectiveness, Utilization, Quality/Safety, Scheduling
    e. SETP uses the SETP Data Submission Tool (an Excel template) to collect information about OR performance across Ontario

ATC Data Quality and Compliance Processes for WTIS and SETP

Data quality is a partnership between facilities/surgeon's offices and ATC – each playing an important role in the process. A robust framework is used to ensure the highest level of data quality is available for performance and public reporting purposes. The cycle consists of:

- Standardized data submission guidelines
- Technical system validations built into tools and templates

- Evidence based data quality management processes
- Clinical expert governance and oversight
- Performance reporting and outreach with stakeholders
- Rigorous feedback mechanisms, support tools and clinical guidance

ATC's data quality management process has been fundamental in ensuring high quality data is reported on for its intended purposes. This process has been successful because it is structured to empower facilities to take accountability of their data quality. This is achieved by:

- Defining data reporting requirements that are specific and relevant
- Providing tools that assist in monitoring data proactively
- Engaging in a monthly follow up process with facilities
- Utilizing clinical experts and stakeholders to help identify issues
- Supporting the management of data quality issues
- Escalating data quality issues to solicit leadership support
- Sharing best practices with facilities to prevent future data quality issues

3) CorHealth Ontario Cardiac Registry (COCR)

a. CorHealth Ontario maintains the CorHealth Cardiac Registry of adult patients who undergo certain advanced cardiac procedures for the purposes of maintaining the waitlist and providing advice to the government for strategic planning.

b. Cardiac procedures included, but not limited to the following:

   i. Cardiac catheterization;
   ii. Percutaneous coronary intervention (PCI);
   iii. Cardiac surgery including coronary artery bypass graft surgery (CABG) and valve surgeries;
   iv. Transcatheter aortic valve implantation (TAVI); and
   v. Procedures related to regulating or assessing heart rhythm including ablations, electrophysiology studies, and procedures relating to certain devices such as implantable cardioverter-defibrillators (ICDs).

c. It contains the following personal health information:

   i. Demographic data
   ii. Health service data
   iii. Wait time data
   iv. Facility data
   v. Healthcare provider data

d. Registry data is used in various ways to inform and support the decisions, recommendations, and quality improvement initiatives made by multiple stakeholders. As such, it is essential to have data that is complete, accurate, and entered according to CCN guidelines. CCN has developed processes and tools to help promote data quality. The maintenance of quality data contained within the Registry requires a continuous and collaborative effort between CCN and hospital stakeholders. Data quality consists of four dimensions: completeness, accuracy, consistency, and timeliness.

e. https://www.corhealthontario.ca/data-&-reporting/data-collection-&-access/CCN-Registries-Data-Entry-Reference-Manual-&-Data-Standards-Document-Updated-September-2017.pdf

4) Trillium's Organ and Tissue Allocation System (TOTAL)

a. TGLN's core information technology system, known as TOTAL, was developed in 2004. The system is mission-critical as it supports Ontario's end-to-end organ donation and transplantation processes, including patient referral, waitlist management, lab result management, organ allocation, organ recovery and transplant and post-transplant. It not only supports internal TGLN program areas but also supports external stakeholders who are required to provide key inputs throughout the organ donation and transplantation process. Users include TGLN's Provincial Resource Centre, transplant hospital clinicians and Human Leukocyte Antigen (HLA) laboratories. The system interfaces with Canadian Blood Service's Canadian Transplant Registry to support national organ donation and transplantation programs.

b. TGLN has established data validation processes to ensure key data elements in TOTAL that are used to support organ donation and transplantation processes, decision making and reporting are complete and accurate. Monthly and quarterly data quality and validation reports are reviewed by TGLN and disseminated to transplant hospital staff who utilize the reports to ensure data entered in TOTAL is complete and matches their internal clinical information systems.

% breakdown of pediatric, cancer and other surgery categories

Surgical service area data from 2019/20 from WTIS for cancer, pediatric and other adult surgery categories used in the paper.

Service Area/Procedure	Percentage (%) of the Total Completed Adult Cancer Surgical Volume in 2019/20
Adult Cancer Surgery Overall	100.0%
Breast	22.8%
Genitourinary (excluding Prostate)	20.3%
Skin - Carcinoma	10.3%
Digestive System - Colorectal	8.6%
Gynaecological	8.4%
Lung	5.3%
Prostate	4.6%
Head and Neck (excluding Thyroid)	4.3%
Skin - Melanoma	3.3%
Endocrine (Thyroid, Endocrine Pancreas, Adrenal)	3.1%
Digestive System - Hepatopancreatobiliary	2.9%
Central Nervous System	2.1%
Sarcoma - Soft Tissue	1.4%
Digestive System - Stomach	0.8%
Digestive System - Esophagus	0.7%
Ophthalmic	0.6%
Sarcoma - Bone	0.4%
Lymphomas	0.1%
Peripheral Nervous System	0.0%

Service Area	Percentage (%) of the Total Completed Pediatric Surgical Volume in 2019/20
Pediatric Surgery Overall	100.0%
Pediatric Otolaryngic Surgery	41.4%
Pediatric Dental/Oral/Maxillofacial Surgery	19.8%
Pediatric Orthopaedic Surgery	8.3%
Pediatric Urologic Surgery	7.8%
Pediatric General Surgery	7.3%
Pediatric Ophthalmic Surgery	7.0%
Pediatric Plastic & Reconstructive Surgery	5.7%
Pediatric Cardiovascular Surgery	1.1%
Pediatric Neurosurgery	1.0%
Pediatric Gynaecologic Surgery	0.8%

Service Area	Percentage (%) of the Total Completed Other Adult Surgical Volume in 2019/20
Other Adult Surgery Overall	100.0%
Ophthalmic Surgery	30.6%
Orthopaedic Surgery	21.3%
General Surgery	15.3%
Gynaecologic Surgery	10.8%
Urologic Surgery	8.3%
Otolaryngic Surgery	5.1%
Plastic and Reconstructive Surgery	5.0%
Oral and Maxillofacial Surgery and Dentistry	1.8%
Neurosurgery	1.4%
Thoracic Surgery	0.4%

Regional data inputs

Legend: Median (IQR)			Health Region			
OR Time (hours)	**Ontario**	**West**	**Central**	**Toronto**	**East**	**North**
Cancer_P2P3	2.0 (1.2, 3.5)	1.9 (1.2, 3.3)	1.6 (1.0, 2.6)	2.9 (1.7, 4.6)	2.0 (1.2, 3.3)	1.7 (0.8, 3.0)
Cancer_P4	1.5 (0.8, 3.0)	1.4 (0.7, 2.9)	1.4 (0.7, 2.5)	2.5 (1.5, 4.1)	1.1 (0.5, 2.6)	1.1 (0.7, 2.0)
Vascular_P2P3	2.1 (1.3, 3.2)	2.0 (1.2, 3.1)	1.9 (1.3, 2.9)	2.9 (1.7, 4.6)	2.0 (1.2, 3.1)	2.4 (1.4, 3.5)
Vascular_P4	1.7 (1.2, 2.8)	1.8 (1.2, 2.9)	1.5 (1.2, 2.3)	2.5 (1.7, 3.8)	1.4 (1.0, 2.2)	1.6 (1.0, 2.4)
Transplant	4.9 (3.8, 7.9)	4.2 (3.6, 4.9)	N/A	6.6 (4.1, 9.0)	4.1 (3.8, 4.8)	N/A
Cardiac_CABG	4.3 (3.7, 5.2)	4.4 (3.9, 5.1)	3.7 (3.3, 4.2)	4.8 (3.9, 5.8)	4.8 (4.1, 5.6)	4.5 (3.9, 5.3)
Cardiac_Valve	4.7 (3.9, 5.8)	4.5 (3.7, 5.5)	4.2 (3.6, 5.1)	5.1 (4.0, 6.4)	5.0 (4.2, 6.1)	4.5 (3.9, 5.4)
Benign_P2P3	1.1 (0.6, 1.7)	1.0 (0.6, 1.6)	1.1 (0.6, 1.6)	1.5 (0.9, 2.5)	1.0 (0.6, 1.7)	1.0 (0.6, 1.7)
Benign_P4	0.8 (0.3, 1.5)	0.7 (0.3, 1.4)	0.7 (0.3, 1.3)	1.3 (0.8, 2.1)	0.7 (0.3, 1.4)	0.7 (0.3, 1.4)
Pediatric_P2P3	1.2 (0.7, 1.8)	1.2 (0.7, 1.9)	0.8 (0.5, 1.3)	1.4 (0.9, 2.7)	1.1 (0.7, 1.6)	1.2 (0.7, 1.6)
Pediatric_P4	0.8 (0.5, 1.3)	0.7 (0.4, 1.2)	0.6 (0.4, 0.9)	1.4 (0.9, 2.3)	0.7 (0.4, 1.2)	0.8 (0.5, 1.2)

			Health Region			
Turnover time (hours)	**Ontario**	**West**	**Central**	**Toronto**	**East**	**North**
All surgery types	0.37 (0.20, 0.55)	0.40 (0.25, 0.55)	0.32 (0.12, 0.50)	0.45 (0.25, 0.63)	0.37 (0.20, 0.53)	0.32 (0.22, 0.47)

			Health Region			
Ward LOS (days)	**Ontario**	**West**	**Central**	**Toronto**	**East**	**North**
Cancer_P2P3	3.0 (1.0, 5.3)	3.0 (1.8, 6.0)	3.0 (1.0, 4.0)	3.0 (1.0, 5.6)	3.0 (1.9, 5.1)	3.0 (2.0, 5.0)
Cancer_P4	2.0 (1.0, 4.0)	2.0 (1.0, 4.0)	2.0 (1.0, 4.0)	2.0 (1.0, 4.0)	2.0 (1.0, 3.1)	2.0 (1.0, 4.0)
Vascular_P2P3	3.0 (1.0, 7.0)	3.0 (1.0, 6.2)	2.0 (1.0, 6.0)	3.1 (1.0, 7.0)	3.8 (2.0, 7.0)	4.0 (1.0, 8.0)
Vascular_P4	2.3 (1.0, 5.0)	2.1 (1.0, 5.0)	3.0 (1.0, 9.0)	2.0 (1.0, 5.0)	2.0 (1.0, 4.0)	1.0 (1.0, 1.0)
Transplant	7.0 (6.0, 11.5)	6.0 (5.0, 8.0)	N/A	8.2 (6.0, 13.8)	6.0 (6.0, 7.0)	N/A
Cardiac_CABG	4.1 (3.1, 6.0)	4.1 (3.1, 5.3)	4.0 (3.0, 5.1)	4.2 (3.2, 6.0)	5.8 (3.9, 9.1)	2.1 (1.9, 3.1)
Cardiac_Valve	4.3 (3.1, 6.2)	4.3 (3.1, 6.1)	4.1 (3.0, 6.0)	4.8 (3.4, 6.1)	5.0 (3.8, 8.0)	2.1 (1.1, 3.2)
Benign_P2P3	2.0 (1.0, 3.0)	2.0 (1.0, 3.0)	2.0 (1.0, 3.0)	2.0 (1.0, 4.0)	2.0 (1.0, 3.0)	2.0 (1.0, 3.0)
Benign_P4	2.0 (1.0, 2.0)	2.0 (1.0, 3.0)	2.0 (1.0, 2.0)	1.0 (1.0, 2.0)	2.0 (1.0, 2.0)	2.0 (1.0, 3.0)
Pediatric_P2P3	2.0 (1.0, 4.5)	2.0 (1.0, 4.0)	1.0 (1.0, 1.0)	2.0 (1.0, 6.0)	1.0 (1.0, 3.0)	1.0 (1.0, 1.0)
Pediatric_P4	1.0 (1.0, 2.0)	1.0 (1.0, 2.0)	1.0 (1.0, 1.0)	1.0 (1.0, 2.0)	1.0 (1.0, 1.0)	1.0 (1.0, 1.0)

			Health Region			
ICU LOS (days)	**Ontario**	**West**	**Central**	**Toronto**	**East**	**North**
Cancer_P2P3	1.8 (1.0, 3.3)	2.0 (1.0, 4.8)	2.5 (1.4, 5.3)	1.1 (0.9, 2.8)	2.1 (1.1, 3.8)	2.1 (1.1, 4.2)
Cancer_P4	1.6 (0.9, 3.0)	1.8 (1.0, 3.6)	2.3 (1.2, 4.2)	1.1 (0.9, 2.6)	1.8 (1.0, 3.4)	1.7 (1.0, 5.2)
Vascular_P2P3	1.8 (1.0, 3.8)	1.8 (0.9, 3.8)	2.1 (1.2, 4.1)	1.0 (0.9, 2.1)	2.1 (1.1, 3.9)	2.1 (1.3, 3.3)
Vascular_P4	1.3 (1.0, 3.0)	1.9 (0.9, 3.5)	1.2 (1.0, 3.0)	1.0 (0.9, 2.0)	2.0 (1.2, 3.1)	N/A
Transplant	3.0 (1.3, 6.5)	7.1 (5.1, 10.2)	N/A	2.8 (1.1, 5.3)	6.0 (5.6, 8.5)	N/A
Cardiac_CABG	1.2 (1.0, 2.2)	1.0 (0.9, 2.0)	1.2 (1.0, 2.0)	1.1 (0.9, 2.9)	1.3 (1.0, 2.7)	2.1 (2.0, 3.1)
Cardiac_Valve	1.5 (1.0, 3.0)	1.2 (1.0, 2.8)	1.3 (1.1, 3.1)	1.2 (1.0, 3.4)	2.0 (1.1, 3.8)	2.1 (2.0, 3.2)
Benign_P2P3	1.9 (1.0, 4.6)	1.4 (0.9, 3.6)	2.7 (1.3, 5.5)	1.8 (0.9, 6.0)	1.8 (1.0, 3.1)	2.8 (1.3, 6.2)
Benign_P4	1.1 (0.9, 2.7)	1.3 (0.9, 2.9)	1.9 (1.0, 3.1)	1.0 (0.9, 2.0)	1.8 (0.9, 3.8)	1.9 (1.0, 3.1)
Pediatric_P2P3	2.1 (1.0, 11.6)	2.2 (1.1, 22.0)	N/A	2.1 (0.9, 9.9)	1.5 (0.9, 7.0)	3.5 (1.8, 5.0)
Pediatric_P4	1.0 (0.8, 2.0)	1.0 (0.9, 2.0)	1.0 (1.0, 1.0)	0.9 (0.8, 1.5)	1.1 (0.9, 5.9)	0.6 (0.3, 0.9)

			Health Region			
% to ward	**Ontario**	**West**	**Central**	**Toronto**	**East**	**North**
Cancer_P2P3	54%	52%	45%	72%	47%	47%
Cancer_P4	50%	48%	48%	75%	36%	21%
Vascular_P2P3	63%	56%	63%	75%	61%	72%
Vascular_P4	42%	48%	34%	64%	30%	21%
Transplant	100%	100%	0%	100%	100%	0%
Cardiac_CABG	100%	100%	100%	100%	100%	100%
Cardiac_Valve	100%	100%	100%	100%	100%	100%
Benign_P2P3	27%	24%	29%	39%	21%	25%
Benign_P4	21%	20%	18%	33%	20%	21%
Pediatric_P2P3	19%	17%	4%	40%	10%	7%
Pediatric_P4	14%	12%	9%	38%	11%	5%

			Health Region			
% to ICU	**Ontario**	**West**	**Central**	**Toronto**	**East**	**North**
Cancer_P2P3	10%	7%	4%	25%	6%	10%
Cancer_P4	5%	3%	2%	13%	3%	2%
Vascular_P2P3	18%	23%	13%	42%	12%	11%
Vascular_P4	13%	12%	14%	24%	6%	0%
Transplant	65%	19%	0%	88%	22%	0%
Cardiac_CABG	99%	98%	100%	100%	100%	100%
Cardiac_Valve	99%	100%	100%	99%	100%	100%
Benign_P2P3	2%	2%	1%	6%	1%	2%
Benign_P4	1%	1%	0%	2%	0%	0%
Pediatric_P2P3	5%	5%	0%	14%	1%	0%
Pediatric_P4	1%	2%	0%	5%	0%	0%

			Health Region			
# of ORs	**Ontario**	**West**	**Central**	**Toronto**	**East**	**North**
Cancer_P2P3	818	251	191	128	178	70
Cancer_P4	818	251	191	128	178	70
Vascular_P2P3	463	100	152	86	76	49
Vascular_P4	463	100	152	86	76	49
Transplant	126	31	0	60	35	0
Cardiac_CABG	131	37	38	21	18	17
Cardiac_Valve	131	37	38	21	18	17
Benign_P2P3	842	252	196	128	193	73
Benign_P4	842	252	196	128	193	73
Pediatric_P2P3	623	202	188	40	132	61
Pediatric_P4	623	202	188	40	132	61

"N/A" means that no surgeries are performed in this health region