For discussion
on 15 April 2014

Legislative Council Panel on Health Services
Subcommittee on Health Protection Scheme

Strategic Review on
Healthcare Manpower Planning and Professional Development –
Commissioned Study on
Projecting Demand and Supply for Healthcare Professionals

PURPOSE

This paper briefs Members on a healthcare manpower projection model developed by the University of Hong Kong (HKU) for the purpose of the strategic review on healthcare manpower planning and professional development.

BACKGROUND

2. As part of our on-going efforts to reform the healthcare system, a high-level steering committee was established in 2012 to conduct a strategic review on healthcare manpower planning and professional development in Hong Kong. Chaired by the Secretary for Food and Health, the steering committee is tasked to formulate recommendations on how to cope with anticipated demand for healthcare manpower, strengthen professional training and facilitate professional development, with a view to ensuring the healthy and sustainable development of our healthcare system. To assist the steering committee in making informed recommendations, we have commissioned HKU to conduct a comprehensive manpower projection for the 13 healthcare professions which are subject to statutory regulation.

3. At the meeting of the Subcommittee on Health Protection Scheme on 11 November 2013, we briefed Members on the common approaches adopted in overseas jurisdictions for forecasting healthcare manpower as well as the constraints and challenges of healthcare workforce planning. We also informed Members of a generic forecasting model being developed by HKU for projecting healthcare manpower in Hong Kong and undertook to provide further details when available.

THE PROJECTION MODEL

4. HKU has completed construction of the manpower projection model for doctors. At the **Annex** is a technical paper produced by HKU explaining the workings of the complex model. In a nutshell, the model seeks to forecast demand for doctors in the planning horizon by projecting healthcare services utilisation of the population to be served using historical utilisation data which are further adjusted for population growth and demographic changes. The demand projections so derived will then be compared with the estimated supply of doctors during the same period to see if any surplus or shortage of manpower exists. The model will be suitably adapted to cater for utilisation parameters peculiar to individual professions in forecasting the manpower demand and supply situation of the other healthcare disciplines under study.

ADVICE SOUGHT

5. Members are invited to note the content of this paper.

Food and Health Bureau
April 2014

<u>Annex</u>

Projecting Demand and Supply for Doctors

1 Modelling of Hong Kong healthcare manpower

The overall model for Hong Kong doctor manpower projection comprises two sub models, the demand model and the supply model. Building on an endogenous, historically-informed base case scenario (where current utilisation (proxying demand) and supply are assumed to be in equilibrium), this model can be adopted to adjust for the impact of externalities such as: 1) de novo (i.e. exogenous) additional new hospital capacity (new public and private hospital in-patient beds) over and above endogenous historical growth and 2) the proposed new Health Protection Scheme. The difference between the demand and supply projections (in terms of total FTE numbers, accumulative and annual incremental FTE from 2012-2041) is the manpower 'gap' or 'surplus/shortfall'.

Modelling of a system (i.e. healthcare system) is driven by two factors: 1) nature of the system and 2) data availability. Modelling is a methodology that describes the interaction of elements inside the system by an equation or a series of equations, in form of numerical and/or logical equations. For systems that can be physically explained, such as the *locus of a free falling object* and the *period of a swing of a simple gravity pendulum*, the corresponding modelling equations can exactly represent reality. However, for the system that cannot be easily explained by physical phenomena, curve fitting (although confounded by interactions between elements/variables) is a common approach. The historical data sample size necessary for obtaining an accurate curve is exponentially proportion to the number of variables included in the model. Although modelling by a full spectrum of variables can truly reflect the nature of the interaction(s), a full spectrum of variables requires a very large data set to derive the best estimate of the interaction(s). Therefore, modelling of uneasily explained systems must accommodate a trade-off between the number of variables and the size of the available data sets. The selection of representative and available variable(s) and the fitting of a numerical expression (model) to these variables is a key issue of system modelling. Examples of commonly used numerical expressions include linear, quadric, exponential, and neural network models. System modelling involves two sets of approximation: approximate full variable spectrum by a limited number of variables and approximate the interactions amongst the variables by (numerical and/or logical) expression(s), to which the modelled system is an approximation of the real system.

Hong Kong healthcare manpower is an extremely complicated system which cannot be easily described by physical phenomena. Therefore, we adopt the ‘curve fitting of historical sample’ approach to model manpower. The core assumption of this model (an essential and common assumption of system models) is that the manpower projection follows historical trends in the data.

2 Projecting doctor demand

2.1 Demand indicators

Parameters for demand model projections

For the public sector, all HA age-, sex-specific in-patient discharge records (2004 to 2011; including day case, A&E, acute care in-patient and long stay) and all age-, sex-specific outpatient visits (for general and specialist outpatients, 2005-2011) and DH service attendances (2005-2011) are available for the healthcare utilisation projections. For the public sector model only, data from 2005 are used, as the data prior to these years would have been unduly influenced by organisational change within the HA and by the SARS epidemic. Table A1 and Table A2 in Annex 1 specifies the variables, parameterisation and data sources. Attendances for DH clinical service units are age-, sex-specific and grouped by service type.

For the private sector, private hospital age-, sex-specific in-patient discharge records (2007-2011: including day case and acute care in-patient) are used as utilisation trends and data available prior to 2007 were of inconsistent quality. Age-, sex-specific outpatients visits from the THS 2005, 2008, 2009 and 2011 are used for the private sector outpatient utilisation projections with adjustment for underreporting.

Discharge rates (day case, acute care, long stay) **-** The discharge rates are based on HA (2005-2011) and private hospital in-patient (2007-2011) discharge records. All age-, sex-specific in-patient (day case (LOS ≤1 day), acute care (LOS > 1 day excluding long stay episodes) and long stay (those designated officially as such) discharges are included.

Outpatient visit rates - HA A&E, general and specialist outpatient visit records per year (2005-2011) and DH service unit attendances (2005-2011) are used to project age-, sex-specific public sector outpatient visit rates. Due to the limited number of data points for private sector outpatient visits (THS data for 2005, 2008, 2009 and 2011) outpatient visit rates for 2006, 2007, and 2010 are estimated using the observed public (HA, excluding A&E and DH) : private outpatient visit proportion as follows:

$$n_{private}^{outpatient}(a,s,y) = n_{HA}^{GOP}\,(a,s,y) \times \,\alpha_{OP}(a,s,THS(y))$$

Eq. 1

where

$n_{private}^{outpatient}(a,s,y)$ is the number of private outpatient visits of age-sex group (a,s) at year y

$n_{HA}^{GOP}(a,s,y)$ is the number of HA-based outpatient visits of age-sex group (a,s) at year y

$\alpha_{OP}(a,s,THS(y))$ is the ratio of private to HA-based outpatient visits of age-sex group (a,s) at the year $THS(y)$

The ratio of private to public outpatient visits for years 2006, 2007, and 2010 (for which no THS was available) are estimated by interpolating from the ratios estimated from THS 2005, 2008, 2009, and 2011. Only HA outpatient visits are included as DH service attendances are seriously under-reported in the THS data. Private sector outpatient visits include solo practice clinics (single practitioner), group practice clinics (multiple practitioners of single or multiple specialties), private hospital outpatient clinics, institutional clinics (charitable organization and 'exempted' clinics), university/tertiary institution clinics and Family Planning Association of Hong Kong clinics.

Although the total number of attendances at the DH clinical service units is available per year (2005-2011), age-, sex-specific visit data are not available for all clinics or for all years. For some services, the age-, sex-specific distribution is interpolated from the distribution of a related service, or estimated from a sample. For example, the age-, sex-specific distribution of Elderly Health Service (EHS) attendances for medical consultations is derived from the distribution of Elderly Health Service attendances for health assessment. For other services, attendance records are available for a limited number of years. The missing data are interpolated from the age-, sex-specific distribution in the nearest year for which data are available assuming no change in attendance patterns.

Total bed-days (acute care and long stay patients) - Average length of stay (ALOS) (total bed-days by age-, sex-specific discharges) is separately calculated for public acute care in-patients and long stay patients, and private acute care in-patients. Age-, sex-specific ALOS for acute care in-patients (length of stay (LOS) > 1 day, excluding long stay[1] episodes) is determined from HA in-patient discharge records (2005-2011) and private hospital in-patient discharge records (2007-2011). Age-, sex-specific ALOS for long stay in-patients (those designated officially as long stay[1] episodes) is determined from HA in-patient discharge records (2005-2011).

2.2 Converting healthcare utilisation to full time equivalents (FTEs)

Two regression-based approaches are used to convert healthcare demand/utilisation to doctor FTEs by service sector (public and private) and by service type (in-patient vs. outpatient, specialist vs. general practitioner).

Hospital Authority

FTE is expressed as a linear combination of utilisation measures:

$$\begin{aligned} FTE_{HA}^{inpatient}(y) &= \left(d_{HA}^{daycase}(y) + d_{HA}^{inpatient}(y) + d_{HA}^{longstay}(y)\right) \times c_{discharge} \\ &+ \left(b_{HA}^{inpatient}(y) - 2d_{HA}^{inpatient}(y)\right) \times c_{inpatient}^{bedday} \\ &+ \left(b_{HA}^{longstay}(y) - 2d_{HA}^{longstay}(y)\right) \times c_{longstay}^{bedday} \end{aligned}$$

Eq. 2

$$FTE_{HA}(y) = FTE_{HA}^{inpatient}(y) + n_{HA}^{SOP}(y) \times c_{HA}^{SOP} + n_{HA}^{GOP}(y) \times c_{HA}^{GOP} + n_{A\&E}(y) \times c_{A\&E}$$

Eq. 3

[1] Long stay episodes fulfil one of the following criteria: discharge specialty denoted by HA as either “infirmary”, “mentally handicapped”, or “psychiatry AND total length of stay >90 days

The workload coefficients $\{c_{discharge}, c_{inpatient}^{bedday}, c_{longstay}^{bedday}, c_{HA}^{SOP}\}$ are estimated by minimizing the sum of difference between the estimated FTE in Eq. 2 and the actual FTE:

$$\left[c_{discharge}, c_{inpatient}^{bedday}, c_{longstay}^{bedday}, c_{HA}^{SOP}\right]$$
$$= arg \min_{[p,q,r,z]} \sum_{y} \left(\left(d_{HA}^{daycase}(y) + d_{HA}^{inpatient}(y) + d_{HA}^{longstay}(y) \right) \times p \right.$$
$$+ \left(b_{HA}^{inpatient}(y) - 2d_{HA}^{inpatient}(y) \right) \times q$$
$$+ \left(b_{HA}^{longstay}(y) - 2d_{HA}^{longstay}(y) \right) r + n_{HA}^{SOP}(y) \times z - D_{HA}^{inpatient}(y)$$
$$\left. - D_{HA}^{SOP}(y) \right)^2$$

Eq. 4

where $D_{HA}^{inpatient}(y)$ is the number of FTE doctors in HA inpatient setting at year *y*, and $D_{HA}^{SOP}(y)$ is the number of FTE doctors in HA SOPD at year *y*.

The workload coefficient of HA GOP visit c_{HA}^{GOP} is estimated as average FTE doctor-to-HA GOP visit ratio:

$$c_{HA}^{GOP} = \frac{1}{7} \sum_{y=2005}^{2011} \frac{D_{HA}^{GOP}(y)}{n_{HA}^{GOP}(y)}$$

Eq. 5

where $D_{HA}^{GOP}(y)$ is the number of FTE doctors in HA GOPD at year *y*.

The workload coefficient of HA A&E attendance $c_{HA}^{A\&E}$ is estimated as average FTE doctor-to-A&E attendance ratio:

$$c_{HA}^{A\&E} = \frac{1}{7} \sum_{y=2005}^{2011} \frac{D_{HA}^{A\&E}(y)}{n_{HA}^{A\&E}(y)}$$

Eq. 6

where $D_{HA}^{A\&E}(y)$ is the number of FTE doctors in HA A&E department at year *y*.

Based on the coefficients the corresponding $\alpha_{workload} = \frac{workload\ on\ inpatient\ care}{workload\ of\ specialist}$ is 0.6. This is consistent with the number of GOP consultations reported in the DH HMS for Doctors (2004-2007 and 2009) and estimates from the HA historical outpatient visit data.

Department of Health

As historical data for the number of DH doctors by service type is not available the DH doctor FTE conversion is calculated as follows:

DH clinic visit workload (except for the Methadone clinics) is assumed to be the same as a HA general outpatient visit. The utilisation of all clinics excluding the Methadone clinics was used to calculate FTE's. Each Methadone clinic (20) is assumed to have one doctor. FTE's are expressed as a linear combination of these utilisation measures:

$$FTE_{DH}(y) = c_{HA}^{GOP} \sum_{i \neq 4} n_{DH}^{i}(y) + 20$$

Eq. 7

Private sector

Although similar methods are used for the private sector doctor FTE conversion, additional parameters are included such as:- the per hospital proportion of resident and visiting doctors, and the proportion of clinic-based non-visiting doctors.

FTE is expressed as a linear combination of utilisation measures:

$$\begin{aligned} FTE_{private}^{inpatient}(y) &= d_{private}^{daycase}(y) \times w_{daycase}^{discharge} + d_{private}^{inpatient}(y) \times w_{inpatient}^{discharge} \\ &+ \left(b_{private}^{inpatient}(y) - 2d_{private}^{inpatient}(y)\right) \times w_{inpatient}^{bedday} \end{aligned}$$

Eq. 8

and

$$FTE_{private}(y) = FTE_{private}^{inpatient}(y) + n_{private}^{outpatient}(y) \times w_{private}^{outpatient}$$

Eq. 9

The workload coefficients $\{w_{daycase}^{discharge}, w_{inpatient}^{discharge}, w_{inpatient}^{bedday}\}$ are estimated by minimizing the sum of difference between the estimated FTE in Eq. 8 and the actual FTE:

$$\begin{aligned}\left[w_{daycase}^{discharge}, w_{inpatient}^{discharge}, w_{inpatient}^{bedday}\right] \\ &= arg \min_{[p,q,r]} \sum_{y} \Big(d_{private}^{daycase}(y) \times p + d_{private}^{inpatient}(y) \times q \\ &+ \left(b_{private}^{inpatient}(y) - 2d_{private}^{inpatient}(y)\right) \times r - D_{private}^{inpatient}(y)\Big)^2\end{aligned}$$

Eq. 10

where $D_{private}^{inpatient}(y)$ is the number of FTE doctors in private hospital inpatient setting at year y.

The workload coefficient of private outpatient visit $c_{private}^{outpatient}$ is estimated as average FTE doctor-to-private outpatient visit ratio:

$$w_{private}^{outpatient} = \frac{1}{7} \sum_{y=2005}^{2011} \frac{D_{private}^{outpatient}(y)}{n_{private}^{outpatient}(y)}$$

Eq. 11

where $D_{private}^{outpatient}(y)$ is the number of FTE doctors in private outpatient clinic at year y

Suppose $D_{private}(y)$is denoted as the number of FTE doctors in the private sector at year y; α_r is the proportion of resident doctor, α_v is the proportion of visiting doctor, α_c is the proportion of clinic-based non-visiting doctor (i.e. $\alpha_r + \alpha_v + \alpha_c = 1$), β is the 'in-patient-outpatient workload' proportion of resident doctor, and λ 'in-patient-outpatient workload' proportion of visiting doctor.

The number of FTE doctors in private hospital inpatient setting $D_{private}^{inpatient}(y)$ is expressed as:

$$D_{private}^{inpatient}(y) = (\alpha_r\beta + \alpha_v\lambda) \times D_{private}(y)$$

Eq. 12

and the number of FTE doctors in private outpatient clinic is expressed as:

$$D_{private}^{outpatient}(y) = (\alpha_r(1-\beta) + \alpha_v(1-\lambda)) \times D_{private}(y)$$

Eq. 13

The value of coefficients α_r, α_v, and α_c are based on the *Private Doctor Survey 2012* conducted by School of Public Health, The University of Hong Kong; β follows the 'in-patient-outpatient workload' proportion of public sector. For λ, the daily activity of a visiting doctor is assumed to be: 10:00 am – 1:00 pm and 3:00 pm – 6:30 pm in clinic, and 2 hours in hospital.

The average number of private outpatient consultations per FTE doctor per day derived from the THS 2009 (data corrected for under-reporting) is used to calculate FTE doctors needed for the projected private outpatient visits from 2012-2041. A linear regression model is used to convert in-patient workload (day case, in-patient discharges, and bed-days) to FTE doctors.

The demand FTEs, $FTE_{demand}(y)$, at year y is calculated as:

$$FTE_{demand}(y) = FTE_{HA}(y) + FTE_{DH}(y) + FTE_{private}(y)$$

Eq. 14

2.3 Modelling doctor demand

After a thorough literature review, assessing the suitability to the local context and exploratory analyses with the various possible projection modes, three approaches for projecting healthcare utilisation are shortlisted for further consideration, the 'empirically observed historical' (EOH), the 'macroeconomic scenario driven' (MSD) and the 'Andersen-type' (Andersen) approach within a 'top down' and 'bottom up' framework (Figure 2.1). Given the lack of required data elements for the Andersen approach, namely detailed individual-level data on predisposing and enabling factors as well as panel studies locally, the two 'top down' approaches are eventually executed.

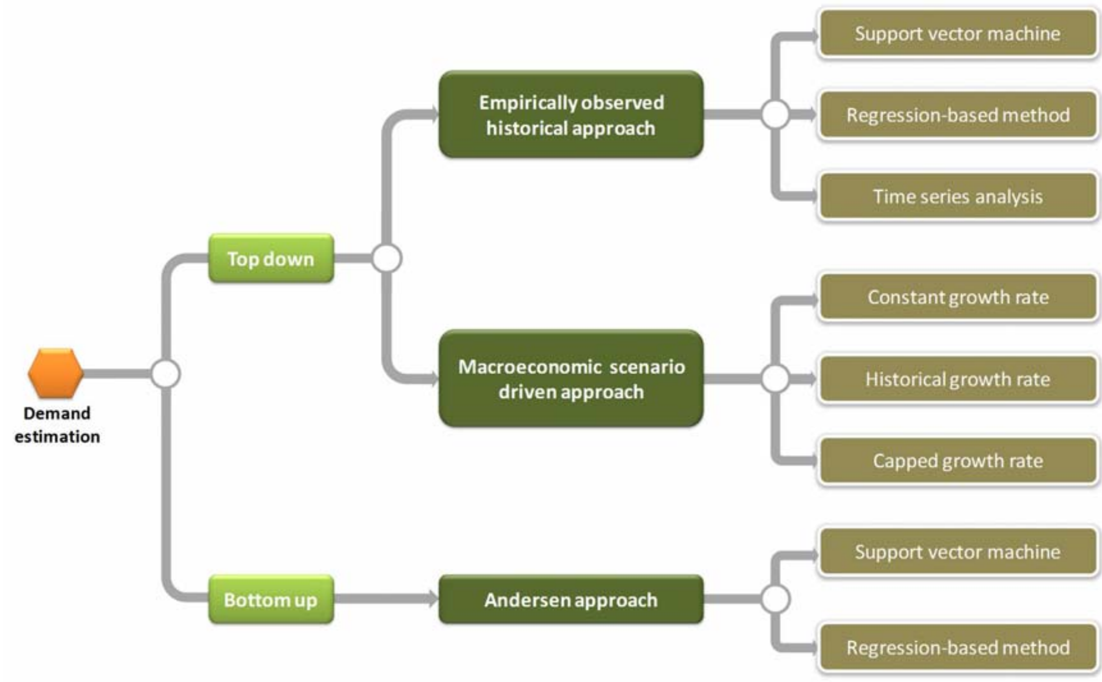

Figure 2.1 Approaches to estimating doctor demand

Support vector machine (neural network analysis), regression-based method, and stock and flow method, are variously deployed to project the required number of doctors as a function of healthcare demand/utilisation and doctor supply to 2041. The projections are stratified by service type (in-patient and outpatient) and by service location (public or private sector).

Empirically observed historical (EOH) approach

The EOH projection model expresses utilisation z(*y*) at year *y* as the product of population *P* and utilisation rate *R*:

$$z(y) = \sum_{a}\sum_{s} P(a,s,y) \times R(a,y|s)$$

Eq. 15

where *P*(*a*,*s*,*y*) is the population age-, sex-specific groups (*a*,*s*) at year *y*, and *R*(*a*, y | *s*) is the utilisation rate by age-, sex-specific groups (*a*,*s*) at year *y*. Census and Statistics Department population projections are used for the projected *P*(*a*,*s*,*y*), historical data inform the computation of *R*(*a*, *y* | *s*).

1. Support vector machine (SVM)

SVM[2] is used to estimate the utilisation rate of each age-, sex-specific group at a given year. SVM is a kernel-based neural network that maps an input x to an output y where w_i is the weight and B is the bias term by the following expression:

$$y = \sum_i w_i \kappa(\mathbf{x}_i, \mathbf{x}) + B$$

Eq. 16

As compared with linear and exponential regression models, SVM has the flexibility to 'evolve' an optimal structure according to historical data. A Gaussian radial basis kernel i.e. $\kappa(\mathbf{x}, \mathbf{y}) = \exp(C\|\mathbf{x} - \mathbf{y}\|)$ is used as it is the 'universal approximator'. The structure is well regularised, and the generalisation ability of the network is maximized.

SVM *learn* the utilisation rate pattern from historical data expressed as:

$$\begin{bmatrix} a_1, s_1, y_1 | r_1 \\ a_2, s_2, y_2 | r_2 \\ a_3, s_3, y_3 | r_3 \\ \vdots \end{bmatrix}$$

where r_i is the utilisation rate of age-, sex-specific group (a_i, s_i) at year y_i. A specific network construction algorithm is designed to evolve the structural parameters $\{w_i\}$ and B. The trained SVM projects the utilisation rate $R(a,s,y)$ of an age-, sex-specific group (a, s) at projection year y = 2012, 2013, …. using the following equation:

$$R(a, y|s) = \sum_{i \, for \, all \, s_i = s} w_i e^{-\frac{(a-a_i)^2 + (y-y_i)^2}{2\sigma^2}} + B$$

Eq. 17

The utilisation volume at year y is computed as:

$$\sum_a \sum_s R(a, y|s) \times P(a, s, y)$$

Eq. 18

where $P(a,s,y)$ is the population size of the age-sex group (a,s) at year y.

[2] Artificial neural networks (ANN) and specifically the Support Vector Machine (SVM) used for these projections are able to predict the complex relationships driving utilisation. Support vector machine (SVM) is a supervised learning method that analyses data and recognizes data patterns in the historical data. As such this artificial intelligence predicts for each given variable the corresponding outcome. SVM was chosen for the projection as it will 'evolve' an optimal structure and estimate the service utilisation of a given individual based on characteristics such as age, and sex.

2. Regression-based method (RBM)

In the RBM approach, $R(a,s,y)$ is estimated by Poisson regression, which assumes:

$$N(a,s,y) \sim Poisson(O(a,s,y)R(a,s,y))$$
$$\log R(a,s,y) = \alpha(a,s) + \beta(a,s)y$$

Eq. 19

where $N(a,s,y)$ denotes the utilisation volume and $O(a,s,y)$ is an offset term in age group a, sex s, and year y. For the projection of all utilisation measures except average length of stay, the population of age group a, sex s, and year y are used for the offset term $O(a,s,y)$. For the projection of average length of stay, the offset term is the number of discharges. Since $\log R(a,s,y)$ is a linear function of y, $R(a,s,y)$ is an exponential function of y, all age- and sex-specific demand variables are included in the Poisson regression. For utilisation measures where there are clear differences in slopes across age-, sex-specific groups (including public and private day case, acute care in-patient discharge and average length of stay (ALOS), as well as HA general outpatient (GOP), specialist outpatient (SOP), accident and emergency (A&E), and private outpatient visits), the projections have age-, sex-specific intercepts and slopes. For all other utilisation measures (public long stay discharge and average length of stay, as well as all DH service visits), the age-, sex-specific intercepts and slopes are constrained to be the same across age and sex groups.

In sensitivity analyses, the Poisson regression projections are compared with projections based on a linear trend. As utilisation rates in linear trend projections may drop below 0, linear projections are used only for utilisation rates that show an increasing trend. The utilisation rate increase is assumed to be the same across all age-, sex-specific groups for SOP, A&E, private outpatient, and all DH visit rates projections lest projections for individual age and sex groups reach zero.

A weighted linear regression is deployed, where the population in age group a, sex s, and year y are used as weights (i.e., $P(a,s,y)$). The following function is minimised with respect to $\alpha(a,s)$ and $\beta(a,s)$.

$$\sum_a \sum_y \sum_s P(a,s,y)(R(a,s,y|s) - \alpha(a,s) - \beta(a,s)y)^2$$

Eq. 20

Projections of rates are given as:

$$\hat{R}(a,s,y) = \alpha(a,s) + \beta(a,s)y$$

Eq. 21

The weights are needed to ensure the estimated age, sex, and year-specific rates $\hat{R}(a,s,y)$ are consistent with the observed rates $R(a,s,y)$.

3. Time series approach

As the elderly and rehabilitation service provision is land-driven, a time-series analysis is used to project the historical growth patterns for elderly and rehabilitation services assuming growth trends $u(y)$ as follows:-

Linear trend

Where the number of places / cases is a linear function of projection year y:

$$u(y) = ay + b$$

Eq. 22

Exponential decay trend

Where the number of applications is expected to decrease exponentially:

$$u(y) = we^{-\alpha y} + c$$

Eq. 23

Constant trend

Where service provision is stable and held constant as at the baseline year:

$$u(y) = u_0$$

Eq. 24

Macroeconomic scenario drive (MSD) approach

As in the EOH-RBM approach, the MSD approach expresses utilisation $z(y)$ at year y as the product of population P and utilisation rate R:

$$z(y) = \sum_a \sum_s P(a,s,y) \times R(a,s,y)$$

Eq. 25

where $P(a,s,y)$ is the age-, sex-specific population (a,s) at year y, and $R(a,s,y)$ is the age-, sex-specific utilisation rate (a,s) at year y. Based on a fixed percentage increase from 2011 levels, population projections of the Census and Statistics Department are used to project $P(a,s,y)$. $R(a,s,y)$ is estimated as follows:-

$$R(a,s,y) = R(a,s,2011) \times (1+x)^{y-2011}$$

Eq. 26

Three methods (constant growth, historical growth, and capped growth) are used to calibrate healthcare utilisation trends against observed data.

4. Constant growth rate

The constant growth rate method sets 'excess healthcare price/cost inflation'[3] growth at 0.2% public sector and 1% for the private sector, consistent with the international literature and to a previous local exercise [1]. The public sector growth rate for each variable is benchmarked to the OECD (1999) [3]. As the OECD reports utilisation growth rates of 0.4% per year, the model assumes a growth rate of 0.2% [4] because half of the growth is due to the net growth in the utilisation rate while the other half is assumed to be due to demographic changes.

Private sector growth rates are benchmarked to OECD (1999) [3] data for the United States and Switzerland, as these two countries predominantly provide healthcare in the private, albeit regulated, sector. The OECD reports an annual growth of 2.7% and 2.4% for the United States and Switzerland respectively. As the healthcare in Hong Kong is equally shared between the public and private sector, the utilisation growth rate in the private sector is assumed to be 1% [4].

[3] The 'excess healthcare price/cost inflation' method is based on the United Kingdom Treasury's Wanless projection method which requires health expenditure to be broken down by age, sex, unit cost and activity level (i.e. volume in terms of healthcare utilisation). The projections take into account aspects of medical inflation (that is medical inflation over and above per capita Gross Domestic Product growth), changes in the utilisation of healthcare services as a result of demographic change, and total health care expenditure (activity levels multiplied by projected unit costs). This comprises two components medical price increase and per capita volume growth according to Huber's review of health expenditure among OECD countries in 1999.

5. Historical growth rate

For the historical growth rate method, 'excess healthcare price/cost inflation' x is estimated from the public and private hospital in-patient discharges and outpatient visits in Hong Kong.

To estimate x, the following function is minimised:

$$\sum_{y} |N(y) - z(y)|$$

Eq. 27

where $N(y)$ is the utilisation volume (number of public and private sector in-patient discharge rates and outpatient visits) and $z(y)$ is the estimated utilisation volume for that year:

$$z(y) = \sum_{a}\sum_{s} P(a,s,y) \times R(a,y|s)$$

$$R(a,s,y) = R(a,s,2011) \times (1+x)^{y-2011}$$

Eq. 28

6. Capped growth rate

As it may be inappropriate to assume ever exponentially increasing utilisation rates, the capped growth rate method is applied to the projection of discharge rates and outpatient (SOP and GOP) visit rates, such that rates would not indefinitely grow exponentially as follows:

$$R(a,s,y) = R(a,s,2011) \times \left(\frac{w}{1+e^{-\alpha(y-y_0-\mu)}} + B\right)$$

Eq. 29

where $R(a,s,2011)$ is the age-, sex-specific utilisation rate for the baseline year 2011, and $\frac{w}{1+e^{-\alpha(y-y_0-\mu)}} + B$ is the general expression of *sigmoid function.*

For average length of stay projections, a biased exponential function is used.

$$ALOS(a,s,y) = ALOS(a,s,2011) \times e^{-\alpha(y-\mu)} + B$$

Eq. 30

where $e^{-\alpha(y-\mu)}$ is the general expression of *biased exponential function*.

The parameters w, α, μ and B are estimated by optimising the objective function:

$$\sum_y |N(y) - z(y)|$$

Eq. 31

as in the historical growth rate model.

Adjusting for under-reporting

THS under-reporting rates for outpatient visits for the public and private sector are estimated for the THS 2002, 2005, 2008, using routine HA and private hospital outpatient visits data (Figure 2.2). Due to data unavailability, estimates of under-reporting rates for private sector outpatient visits is not possible. Private sector under-reporting rates are assumed to be the same as for HA outpatient visits.

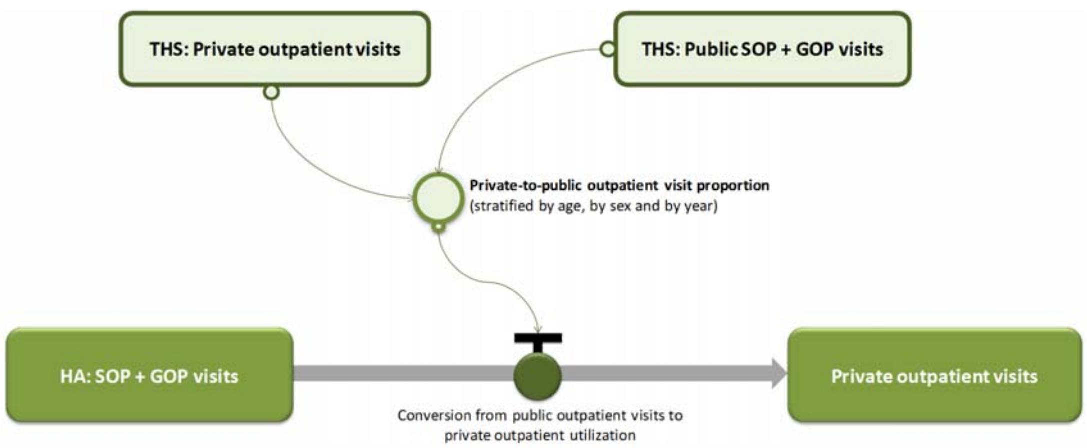

Figure 2.2 Under-reporting adjustment of THS outpatient visit data

Capping rates

The RBM gives exponential rate increases across all utilisation variables. This leads to projections that are too extreme to be realistic beyond the first few years. To address this problem, age-, sex-specific utilisation rates are allowed to continue until 2016 after which they are held constant (i.e. capped) for the rest of the projection period. The discharge and outpatient visit rate caps are benchmarked to the historical OECD utilisation trend data (OECD 2012) [3].

To set the discharge rate cap, the current OECD acute care in-patient discharge rate for Hong Kong (178 discharges/1000 person-year [2]) is compared to OECD individual country trends (Figure 2.3). Hong Kong discharge rate increase is benchmarked to the 90th percentile of the 2011 OECD countries discharge rate (237 discharges/1000 person-year) (representing an average discharge rate increase of 33%). Based on historical data Hong Kong will reach this estimated discharge rate by 2016, after which the discharge rate increase is capped.

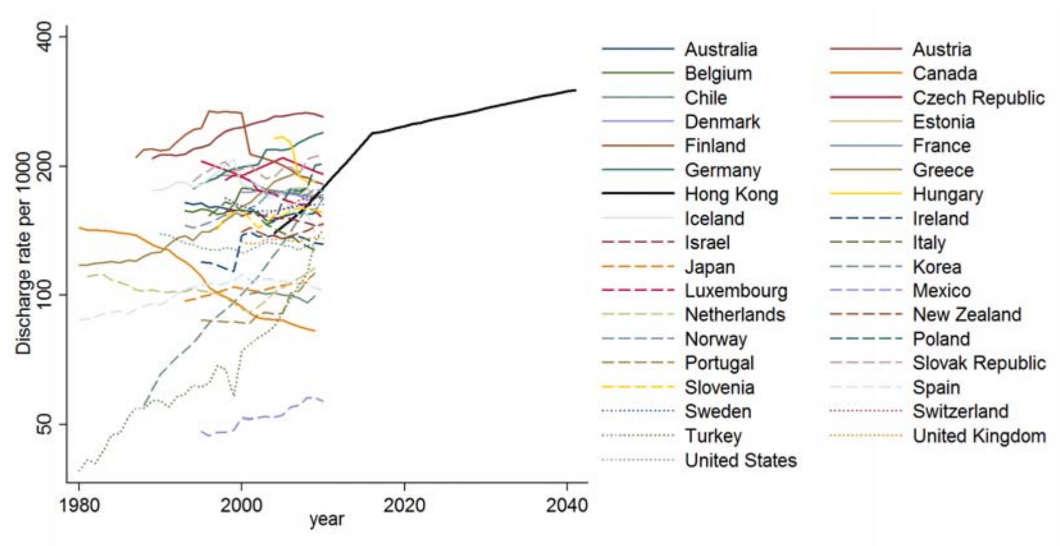

Figure 2.3 Comparison of Hong Kong and OECD acute care in-patient hospital discharge rates (152,153)

Similarly for outpatient visit rates, the doctor visit rate as published by the OECD for HK (2011) (11.2 visits per person-year [2]) is benchmarked against OECD individual country trends (highest rate 13.1 visits per person per year in Japan) (Figure 2.4). Based on this comparison, Hong Kong outpatient visit rates are expected to increase by 17% and will reach this target by 2016. The outpatient visit rate is capped after 2016.

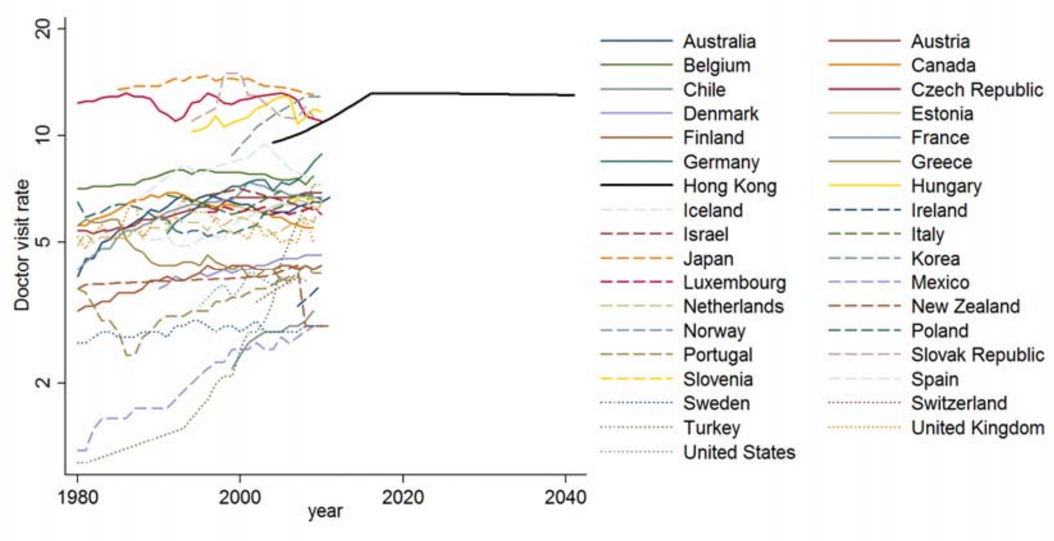

Figure 2.4 Comparison of Hong Kong and OECD doctor outpatient visit rates [2] [3]

2.4 Model comparison

The top down methods (EOH and MSD), with relatively fewer data requirements, are based on the expectation that simple, aggregate models provide more reliable and reproducible healthcare utilisation projections. Further consistent, comprehensive data (number of observations and data-points) are available for the public sector. Much less reliable data are available for the private sector.

The performance of a model is represented by the sum of absolute rate error $E(\theta, u)$:

$$E(\theta, u) = \sum_a \sum_y \sum_s \left|\widetilde{M_u}(a, s, y|\theta) - R_u(a, s, y)\right|$$

Eq. 32

where $E(\theta, u)$ is the sum of absolute rate error of model θ ∈ {EOH-SVM, MSD-constant growth rate, MSD-historical growth rate} on utilisation u

$\widetilde{M_u}(a, s, y|\theta)$ is the estimated utilisation rate on u of age-sex group (a, s) at year y by model θ and

$R_u(a,s,y)$ is the actual utilisation rate on u of age-sex group (a, s) at year y.

Note that the index y in the formulate of $E(\theta,\ u)$ has different range for different utilisation measures: $y \in \{2005, 2006, \ldots, 2011\}$ for public sector and private outpatient utilisation; and $y \in \{2007, 2008, \ldots, 2011\}$ for private sector inpatient utilisation. Table 3.3 lists the estimation error of EOH-SVM, MSD-constant growth rate and MSD-historical growth rate. The EOH-SVM models give a better model fit than the MSD models (Table 2.1). The EOH-SVM estimation errors are smaller than those for the MSD-constant growth or MSD-historical growth rate models.

Table 2.1 Comparison of EOH-SVM, MSD-constant growth, MSD-historical growth rate estimation errors

	EOH-SVM	MSD (constant growth rate)	MSD (historical growth rate)
Day case discharge rate (public)	0.93	7.56	1.53
Acute care in-patient discharge rate (public)	0.82	3.83	2.05
Acute care in-patient bed day rate (public)	7.29	44.65	17.19
Long stay discharge rate (public)	0.03	0.08	0.05
Long stay bed day rate (public)	11.09	28.42	20.21
SOP visit rate	3.67	8.09	8.08
GOP visit rate	4.04	16.95	10.06
A&E attendance rate	2.26	5.30	4.69
Day case discharge rate (private)	0.18	0.57	0.48
Acute care in-patient discharge rate (private)	0.11	0.42	0.33
Acute care in-patient bed day rate (private)	1.06	2.45	2.28
Private outpatient rate	99.03	252.69	251.94

In a sensitivity analysis, as would be expected, the EOH-RBM linear based model gives projections that are less steep than the Poisson model (which assumes an exponential trend) however, the data do not support a linear trend more than an exponential trend. The mean squared error is smaller for most utilisation measures projected by the RBM-Poisson model (

Table 2.2). To avoid negative values, age-, sex-specific utilisation measures in the RBM linear model, share the same intercepts and slopes.

Table 2.2 Comparison of the linear and exponential RBM utilisation projections mean squared error (MSE) for selected demand/utilisation variables.

Demand/utilisation variables	Natural scale		Log scale	
	Linear	*Exponential*	*Linear*	*Exponential*
Public day cases	25.8	**18.0**	0.0038	**0.0026**
Public specialist outpatient visits	700	**522**	0.0014	**0.0007**
Public general outpatient visits	1189	**830**	0.0038	**0.0017**
Accident and Emergency visits	165.4	**125.8**	0.0021	**0.0016**
Private day cases	**1.63**	1.76	**0.0029**	0.003
Private acute care in-patient discharges	**6.13**	6.69	0.0028	**0.0013**
Private outpatient visits	771405	**561993**	0.032	**0.026**
DH Student and child services	1022	**982**	1.21	**0.09**
DH Port Health Office	0.20	**0.18**	0.18	**0.05**

SVM models have the ability to generalize, learn from examples, adapt to situations based on historical data and generalize patterns from historical data in response to unknown situations. SVM implicitly detects complex nonlinear relationships between independent and dependent variables. When responding to nonlinearity between the predictor variables and the corresponding outcomes, the model automatically adjusts its structure to reflect these nonlinearities. The predictor variables in SVM undergo multiple nonlinear transformations and can thereby potentially model much more complex nonlinear relationships than RBM.

Regression models can also be used to model complex nonlinear relationships. However, these models require an explicit search for these relationships by the model developer and these may not be known or well understood. Appropriate transformations may not always be available for improving model fit, and significant nonlinear relationships may go unrecognized by model developers.

When complex data and relationships are involved, as compared to RBM, SVM would in theory at least, and empirically shown by the model fit statistics above, provide a more robust projection outcome, more flexibly integrates complex data into the model, and is not dependent on a pre-determined hypotheses about the relationships between model variables. For these reasons, the EOH-SVM approach has been used for all model projections in the report.

3 Projecting doctor supply

Hong Kong Medical Council doctor registration data (age-, sex-specific) for 2012 [5] –[6] is used for the doctor supply base case. The University Grants Committee data for past and projected number of local medical student graduates and data from the DH Healthcare Manpower Survey (HMS) [7] - [11] for Doctors (with the public sector proportion adjusted to be consistent with the actual by the HA doctor employment records [Statistical Report [12] from 2005 – 2007, 2009) are used for the supply projections.

3.1 Models for doctor supply

The doctor supply model is a non-homogenous Markov Chain Model (MCM)[4], where workforce systems are represented as "stocks and flows" (Figure 3.1). Flow refers to manpower supply over a period of time. Stock denotes manpower supply at a particular point in time.

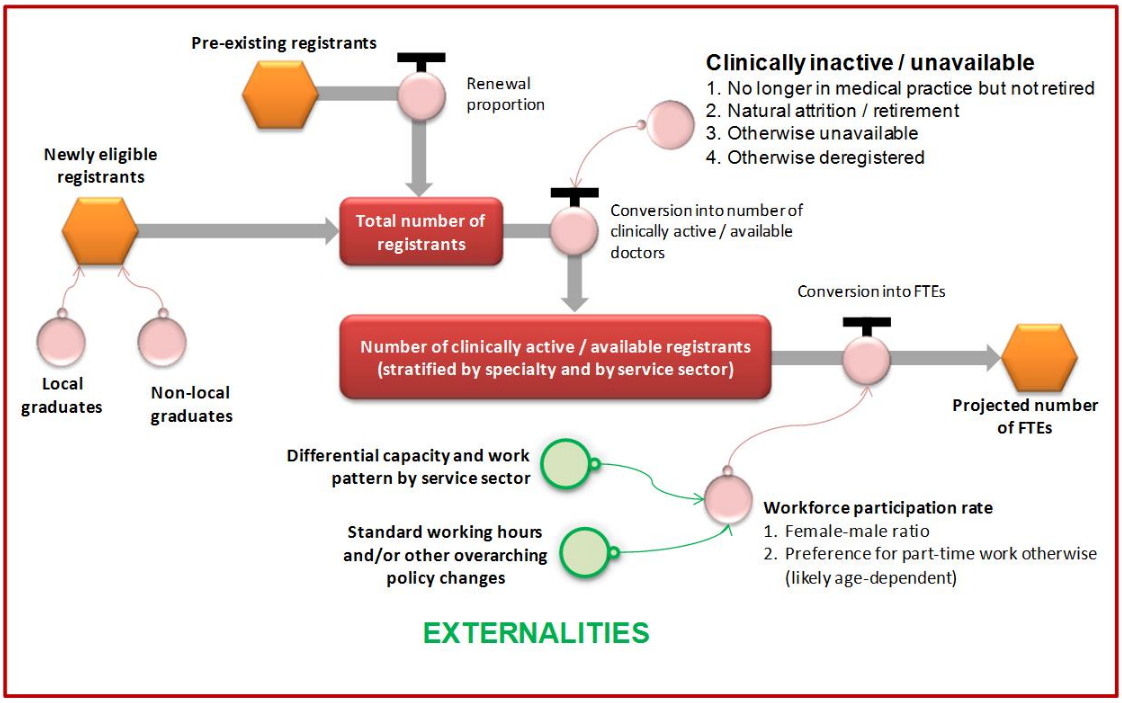

Figure 3.1 Doctor supply model for Hong Kong.

[4] Markov Chain Model (MCM): MCM estimates transition probabilities relevant to manpower stock and flow and is useful for micro level manpower planning

There are five age-sex specific stocks by year (a,s,y) in the model:

n_{pre}	number of pre-existing registrants
n_{local}	number of local graduates
$n_{non\text{-}local}$	number of non-local graduates
$n_{current}$	number of current registrants
n_{active}	number of active and available registrants

Flow in the supply model represents change in the stocks and is projected by determining:

<u>The number of current registrants</u> (total number of local graduates, non-local graduates and pre-existing registrants):

$$n_{current}(a,y,s) = p_{renewal} \times n_{pre}(a,y,s) + n_{local}(a,y,s) + n_{non-local}(a,y,s)$$

and

$$n_{pre}(a,y,s) = n_{current}(a,y-1,s)$$

Eq. 33

where $p_{renewal}$ is the licence renewal proportion.

<u>The number of active and available registrants</u>:

$$n_{active}(a,y,s) = n_{current}(a,y,s) \times p_{active}(a,s)$$

Eq. 34

where $p_{active}(a,s)$ is the active proportion of age-sex group (a,s).

3.2 Determinants of supply: projecting stock and flow

<u>Total number of registrants</u>

The total number of registrants is defined as the number of pre-existing registrants (pool of registered doctors multiplied by the registration renewal proportion [as provided by the HKMC]) and the newly eligible registrants (new medical graduates from the University of Hong Kong (HKU) and the Chinese University of Hong Kong (CUHK), new provisional licences [for medical interns]) and non-local graduates entering the pool by year (2005-2011).

Based on the number of medical student placements (set by the UGC) and the expected number of provisional licences for medical interns, the number of new registrants are projected using a sigmoid function. The supply model thus assumes a cap on medical student graduation at 420 students from 2019 – 2041. Although data are available for the HKMC (2001-2011) licensing examination pass rates, based on the current (2012) number of non-local registrants, the supply model assumes a constant inflow of 60 non-local graduates to the registration pool per year, that is in line with the latest year statistics.

Number of clinically active registrants

Although the total number of registrants adds to the total doctor pool, it is the number of clinically active/available[5] registrants that is relevant for workforce projection. The supply model stratifies clinically inactive/unavailable doctors into four categories: no longer in medical practice but not retired, natural attrition/retirement, otherwise unavailable, and otherwise deregistered. Based on the HMS on Doctors [7] - [11], a sigmoid function is used to project the number of doctors who are no longer in medical practice but not retired, doctors who leave due to natural attrition/retirement, and those otherwise unavailable. Based on HKMC data [5] [6], one doctor is assumed deregistered each year.

3.3 Converting workforce supply to full time equivalents (FTEs)

The model uses the age-, sex-specific stratified average working hours to determine the total hours worked by sector. The average working hours in any sector is capped at 65 hours per week (equivalent to 1 FTE).

[5] The definition for clinically active/available doctors varies from that adopted by the DH. We have excluded doctors who are no longer in medical practice but not retired, those otherwise unavailable from the clinically active and available, and those deregistered.

The supply FTEs, $FTE_{supply}(y)$, at year y is calculated as:

$$FTE_{supply}(y) = \frac{\sum_a \sum_s (n_{active}(a,y,s) \times \sum_c p_{sector}(a,s,c) \times h(a,s,c))}{Standard\ working\ hours\ per\ week\ per\ FTE}$$

Eq. 35

where $p_{sector}(a,s,c)$ is the proportion of doctors working in the service sector c at year y, and $h(a,s,c)$ is the average number of working hours per doctor.

The supply projection is based on the stocks and also the parameters $p_{renewal}$, $p_{active}(a,s)$, $p_{sector}(a,s,c)$ and $h(a,s,c)$. A sigmoid model is used to project the parameters.

4 Gap analysis

The gap analysis quantifies the difference between the projected demand for and supply of doctors for the base case (assumed demand and supply is at equilibrium from 2005 – 2011, i.e. realised demand equals realised supply where the gap is defined to be zero).

For the supply base case, the projected FTE supply includes only those working in the HA, the private sector, and the DH. As the data available do not separately report DH headcount, the model assumes that 30% of the 'Government, academic, and subvented' headcount are attributable to the DH. Others in the 'Government, academic, and subvented' category are not included in the gap analysis supply projections.

The gap analysis used a top down approach for FTE conversion, based on empirical data and using regression-based methods determined an in-patient-outpatient workload proportion of 0.6.

Three methods (annual number of FTEs, year-on-year FTE, and annual incremental FTE) are used to quantify FTE doctor demand and compared to the base case supply projections.

Annual number of FTE

The number of FTE doctors in year y is stratified into the number of FTE demand doctors and the number of FTE supply doctors. Their expressions are shown in Eq. 14 and Eq. 35 respectively.

Year-on-year FTE

The year-on-year FTE method quantifies the accumulated difference between demand and supply as follows:-

$$a(y) = FTE_{demand}(y) - FTE_{supply}(y)$$

Eq. 36

where $a(y)$ is the year-on-year FTE at year y, FTE_{demand} and FTE_{supply} are the demand and supply FTE at year y shown in Eq. 14 and Eq. 35 respectively.

Annual incremental FTE

The annual incremental FTE method quantifies the change in the demand supply gap from the previous year as follows:-

$$I(y) = a(y) - a(y-1)$$

Eq. 37

where $I(y)$ is the annual incremental FTE at year y, and $a(y)$ is the year-on-year FTE at year y shown in Eq. 36.

5 Assumption

5.1 Demand side

i. We adopt the 'curve fitting of historical sample' approach to model the manpower, the projection is assumed to follow the historical trend in the data.

ii. For the THS private outpatient visits, we assume that the age-sex specific under-reporting rates of private outpatient visit and public general outpatient visit are equal.

iii. The data from five THSs is assumed to be sufficient to represent the historical trend of private outpatient visit.

iv. The data from seven-year HA patient record is assumed to be sufficient to represent the historical trend of HA-based healthcare utilisation pattern.

v. In the estimation of workload coefficients, we assume that demand and supply are balance.

vi. The workload coefficients are assumed to be time-invariant.

5.2 Supply side

i. The number of local graduates from 2019 to 2041 follows that at 2018.

ii. The licence renewal proportion $p_{renewal}$ is assumed to be age-, sex- and time-invariant.

iii. The active proportion $p_{active}(a,s)$ is assumed to be time-invariant.

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Annex 1

Table A1 Demand model variables, parameterisation and data sources

Variables		**Parameterisation**[2]	**Data source**
Population to be served			
Resident population		Age- sex-stratified	C&SD 1999 through 2011
Population forecast		Age- sex-stratified	C&SD population projections 2012 - 2041
In-patient			
Number of day cases			
Public sector	$d_{HA}^{daycase}$	Age- sex-stratified	HA records 2005-2011
Private sector[1]	$d_{private}^{daycase}$	Age- sex-stratified	Hong Kong private hospitals 2007-2011[1]
Number of acute discharges			
Public sector	$d_{HA}^{inpatient}$	Age- sex-stratified	HA records 2005-2011
Private sector[1]	$d_{private}^{inpatient}$	Age- sex-stratified	Hong Kong private hospitals 2007-2011[1]
Number of long stay discharges			
Public sector	$d_{HA}^{longstay}$	Age- sex-stratified	HA records 2005-2011
Number of acute care bed-days			
Public sector	$b_{HA}^{inpatient}$	Age- sex-stratified	HA records 2005-2011
Private sector[1]	$b_{private}^{inpatient}$	Age- sex-stratified	Hong Kong private hospitals 2007-2011[1]
Number of long stay bed-days			
Public sector	$b_{HA}^{longstay}$	Age- sex-stratified	HA records 2005-2011

Table A2 Demand model variables, parameterisation and data sources

Variables		Parameterisation[2]	Data source
Outpatient			
Number of HA GOP visits	n_{HA}^{GOP}	Age- sex-stratified	HA records 2005-2011
Number of HA SOP visits	n_{HA}^{SOP}	Age- sex-stratified	HA records 2005-2011
Number of HA A&E attendances	$n_{HA}^{A\&E}$	Age- sex-stratified	HA records 2005-2011
DH service unit attendances	n_{DH}^{i}	Age- sex-stratified by service unit $\{i\}$	Department of Health 2005-2011
Number of private outpatient visits	$n_{private}^{outpatient}$	Age- sex-stratified	THS 2005, 2008, 2009, 2011 (Adjusted for under reporting using HA outpatients records 2005-2011)

[1]Private hospitals: Evangel Hospital, Hong Kong Adventist Hospital, Hong Kong Baptist Hospital, Hong Kong Central Hospital, Hong Kong Sanatorium and Hospital, Matilda International Hospital, Precious Blood Hospital, St Paul's Hospital, St Teresa's Hospital, Tsuen Wan Adventist Hospital, Union Hospital, The Canossa Hospital

[2]All data were stratified by age and sex groups in 5-year age categories.

Annex 2

Reference

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