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# Worth the wait: The impact of government funding on hospital emergency waiting times 

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#### Abstract

In the absence of a price mechanism, emergency department waiting times act as a rationing device to equate demand for treatment with available supply. Sustained increases to demand stemming from population growth, aging populations, and rising comorbidities has caused waiting times internationally to rise. This has resulted in increased calls for higher funding from governments and commitments from both state and national governments to address excessive waiting times. This paper aims to determine the effectiveness of government funding for improving the median waiting times for treatment and the proportion of patients seen within clinically recommended waiting times. For this purpose, an econometric analysis was conducted on a panel of data on Victorian local health networks over the period 2015-2018. This is supplemented with a discussion of the alternative measures which governments might take to both address demand for emergency treatment, and also ensure that waiting time reductions can be maintained over the long-term.


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In hospital emergency departments, the absence of a formal price mechanism to equate the demand for treatment with the available supply means that waiting times act as a rationing device [1]. The prioritisation of patients is typically based on the severity of symptoms and the urgency of care required, and patients experience waiting times in a 'queue' where they must be physically present at the emergency department to receive treatment [2].

Temporary fluctuations in waiting times occur based on demand patterns such as time, day, or season (e.g. influenza season) [2,3] or atypical events such as natural disasters, pandemics (such as the recent COVID-19 outbreak), staffing disruptions or other shocks [4]. However, it has been recognised that increased pressure is being placed on emergency departments resulting from sustained increases in presentations. These sustained increases largely stem from population growth, aging populations, and greater risk factors within the wider community (including greater incidence of comorbidities) [3,5].

Without a corresponding increase to the capacity of emergency departments- via investment in additional physical or human resources [3,6] - waiting times must inevitably increase until a

[^0]new equilibrium is established, a trend which is currently being seen internationally [7].

Increased waiting times are concerning given the potential for deteriorations in health, reduced effectiveness of treatment, and increased likelihood of adverse health events (i.e. mortality and morbidity) [8]. Given these weighty potential implications, many health-related organizations consider the current level of government funding inadequate and have called on governments to raise the level of public funding. For example, the Australian Medical Association [9, p.3] commenting on wait times argued that:

We must force all Governments to address this, immediately. It will take time, funding, and planning but this is no excuse to delay significant activity in rectifying the situation. While we support efficient hospitals, we must deliver effective ones.

This sentiment has been increasingly recognised by governments at both the state and national level. Evidence can be seen through the promises made by politicians to provide additional funding to facilitate reductions in waiting times, and to ensure a higher percentage of patients are seen within clinically recommended waiting times:
"[emergency departments] are over-crowded and underfunded.... One in three patients with an urgent condition doesn't get seen within the recommended time... we will put in
\$500 million to upgrade Emergency Departments and to bring down waiting times, right across Australia" [10]

To achieve these commitments, policymakers must make informed decisions on the appropriate quantum of funding, as well as the optimal waiting time levels and the hospitals which should be targeted with additional support. However, before these decisions can be made it is important to have an understanding of whether government funding can create material reductions in waiting times, and the magnitude of reductions which might be expected. Although the literature has examined other factors which may influence waiting times - including external determinants (such as demand shocks and availability of substitutes) [4,11,12], impact of non-financial government policy and internal policy changes [13-15] - the impact of funding has not yet been sufficiently identified.

To address this gap, and to support informed decision-making, an econometric analysis of the association between government funding and median waiting time for emergency treatment has been undertaken, using available data on Victorian local health networks (LHNs). This has been supplemented by an analysis of the association between funding and the percentage of patients seen within clinically recommended waiting times, which may represent a desirable target for policymakers given its importance as a key priority for LHNs (see the Statement of Priorities; [16]). Moreover, a discussion of the additional support which governments may provide to assist LHNs to maintain waiting time reductions over the long-term has also been included. Thus, Section 2 outlines the data used in the econometric estimations, and the results are presented in Section 3. Finally, a discussion and concluding remarks are provided in Sections 4 and 5, respectively.

## 1. Methodology

To test the impact of funding on waiting times for emergency treatment, we employed a four-year panel of Victorian public LHN data. LHNs were selected for the analysis as they are the principal recipient of government funding in Australia, owing to the small size of many regional and rural hospitals which limits their administrative and financial capacity.

As panel data is available, the use of a fixed or random effects estimator is generally indicated. Given that the Hausman test did not indicate correlation between the explanatory variables and error term $(\mathrm{p}=0.867)$, a random effects model was employed:

$$
\begin{equation*}
\boldsymbol{T}_{\boldsymbol{i t}}=\alpha_{i t}+\beta_{1} \boldsymbol{G}_{\boldsymbol{i t}}+\beta_{2} \boldsymbol{X}_{\boldsymbol{i t}}+\mu_{i t} \tag{1}
\end{equation*}
$$

Where $\mathbf{T}$ is the median waiting time (in minutes) spent in the emergency department from arrival to departure, either through admission, discharge, or transfer to another hospital. $\mathbf{G}$ is the amount of grant funding received from federal and state governments. Notably this amount is restricted to the emergency department component of total grant funding and thus does not include additional funding associated in-patient treatment (which is determined separately based on diagnostic groups and a Weighted Inlier Equivalent Separations (WIES) system). $\mathbf{X}$ is a vector of control variables and $\mu$ is an independent and identically distributed error term. The $i$ and $t$ subscripts refers to the individual LHN and year, respectively. In supplementary models which examine the association between funding and the percentage of patients seen within clinically recommended waiting times (as a suitable policy target), the same specification is employed, however in these models $\mathbf{T}$ represents the percentage of patients seen on time.

One concern which has been raised in the literature [2,6] relates to the potential for endogeneity between funding and waiting times or waiting time targets. If funding levels are themselves
influenced by waiting times, measures related to waiting times (such as the percentage of patients seen on time), or a common unidentified factor, this can create bias in the estimators obtained. This is particularly important in systems which explicitly include a measure of waiting times in formula-based grant allocations. Emergency department funding in Victoria is determined by the number of presentations, national urgency related group (URG) and urgency disposition group (UDG) cost weights (cost weights assigned to emergency department presentations; with loadings for indigeneity and location) and the national efficient price, and thus does not directly account for waiting times or targets. Therefore, the potential for bias is small, albeit not be negated completely [17]. Accordingly, to ensure any potential bias is accounted for, an instrumental variable (IV) model was also employed. For this purpose, the average URG and UDG price weights applied to each LHN to determine funding levels were selected as instruments.

The control variables selected conform to the theoretical expectations and extant literature. The number of patients treated by triage category were included to account for the demand faced by EDs and clinical urgency which can reduce the waiting time for the patient (if they are given a higher triage category) whilst potentially raising the waiting times for patients with lower triage categories [18]. The number of full-time equivalent (FTE) staff, categorized into nurses and medical officers, and staff involved with administrative functions were also incorporated to account for available human resources. Similarly, the size of the hospital, represented by the number of beds available was employed to account for the capital resources [19]. As this variable is measured on an ordinal scale, four indicator variables were created (small (<100), medium (100-199), large (200-499), and very large (>500)).

In addition to hospital characteristics, community demographics and risk factors were required. The percentage of children (under 15) and elderly (over 65) were chosen due to the higher incidence of acute conditions in these age groups [8]. The percentage of indigenous residents (i.e. those who identify as Aboriginal or Torres Strait Islander (ATSI)) was used to account for the differences in funding arrangements (that is, ATSI status of patients is taken into account in determining funding amounts) [8]. To control for the residency status of patients and the ability to pay for additional medical services (i.e. transport to the hospital and required medication) - which may result in an increased willingness to utilize health services - the percentage of Australian citizens and median income (including government payments and allowances) were also employed.

Risk variables, including the percentage of daily smokers, excessive alcohol consumers (i.e. those that exceed the recommended guideline of 2 standard drinks per day on average), or overweight/obese persons (body mass index (BMI) above 25) were used to control for the increased likelihood of developing acute or chronic diseases (for example lung cancer, liver damage, and diabetes) [5]. Finally, indicator variables representing (i) whether the LHN is in an urban or rural area (urban $=1$ ), (ii) individual years under analysis, and (iii) seasonal weights were included to account for patterns of demand. Where necessary natural log transformations were applied to correct for skewed variable distributions (based on results from standard econometric testing, including normality testing, ladder-of-powers testing, and quantile plot analysis). Descriptive statistics for the variables are presented in Table 1:

Data was sourced from the annual reports and accompanying financial statements of the respective LHNs, the AIHW MyHospitals databases, the AIHW Australia's Health reports, and the ABS National Regional Profile [5,20,21].

Table 1
Variables Employed.

| Variable | Definition | Mean | Standard Deviation |
| :---: | :---: | :---: | :---: |
| Median Waiting Time (all patients) | Waiting time for treatment (in minutes) | 165.82 | 34.47 |
| Tri 1 | Number of Triage 1 (resuscitation) patients | 286.71 | 299.19 |
| Tri 2 | Number of Triage 2 (emergency) patients | 6203.58 | 6790.77 |
| Tri 3 | Number of Triage 3 (urgent) patients | 19883.68 | 19199.98 |
| Tri 4 | Number of Triage 4 (semi-urgent) patients | 22277.62 | 17852.98 |
| Tri 5 | Number of Triage 5 (non-urgent) patients | 4025.09 | 3018.42 |
| Nurses and Medical Officers (ln) | Number of FTE nurses and medical officers | 6.94 | 1.01 |
| Admin (ln) | Number of FTE administration, allied, ancillary and support staff | 6.86 | 0.93 |
| Small | Hospitals with less than 100 beds | 0.16 | n/a |
| Medium | Hospitals with between 100 and 199 beds | 0.21 | n/a |
| Large | Hospitals with between 200 and 499 beds | 0.25 | $\mathrm{n} / \mathrm{a}$ |
| Very Large | Hospitals with more than 500 beds | 0.38 | n/a |
| Under 15 (ln) | Percentage of residents under 15 | 2.83 | 0.24 |
| Over 65 | Percentage of residents over 65 | 16.66 | 4.54 |
| ATSI (ln) | Percentage of Aboriginal and Torres Strait Islander residents | -0.07 | 0.84 |
| Australian Citizens | Percentage of residents with Australian citizenship | 84.40 | 9.66 |
| Median Income (\$) | Median income received by residents | 42547.3 | 4936.81 |
| Daily Smoker | Percentage of residents who smoke on a daily basis | 12.45 | 3.05 |
| Drinking (ln) | Percentage of residents who exceed the lifetime risk level of alcohol | 4.04 | 0.14 |
| Overweight | Percentage of residents with a BMI above 25 | 49.43 | 6.18 |
| Total Grant (\$10,000 s) | Total grant funding from State and Federal governments | 29.48 | 27.71 |
| Urban | Location of the LHN: 1 if LHN is in an urban area; 0 otherwise | 0.42 | n/a |

Table 2
Impact of Grant Funding on Median Waiting Times, Victorian LHNs, 2015-2018.

|  | Model 1 (RE) | Model $2($ IV $)$ |
| :--- | :--- | :--- |
| Total Grant $(\$ 10,000 \mathrm{~s})$ | $-1.543^{* *}(0.523)$ | $-2.311^{* *}(0.394)$ |
| Tri 1 | $0.080^{* *}(0.018)$ | $0.092^{* *}(0.014)$ |
| Tri 2 | $-0.0005(0.002)$ | $-0.0009(0.002)$ |
| Tri 3 | $0.003^{*}(0.001)$ | $0.004^{* *}(0.001)$ |
| Tri 4 | $-0.002^{* *}(0.0006)$ | $-0.002^{* *}(0.0005)$ |
| Tri 5 | $0.005^{*}(0.002)$ | $0.006^{* *}(0.002)$ |
| Nurses and Medical Officers | $-39.256^{+}(21.379)$ | $-44.758^{* *}(15.805)$ |
| $\quad$ (ln) |  |  |
| Admin (ln) | $34.300^{*}(14.802)$ | $42.189^{* *}(11.518)$ |
| Overweight/Obese | $1.104^{+}(0.640)$ | $1.216^{* *}(0.491)$ |
| Controls | Yes | Yes |
| N | 88 | 88 |
| Coefficient of Determination | 0.8348 | 0.8295 |
| $\quad$ (overall) |  |  |

Robust standard errors in parentheses.
${ }^{+} \mathrm{p}<0.10$.

* $\mathrm{p}<0.05$.
${ }^{* *} \mathrm{p}<0.01$.


## 2. Results

Table 2 reports the results of our regression of hospital attributes, community characteristics, and funding levels on median waiting time for treatment (full results presented in Table A1). Preliminary testing rejected the existence of underidentification and weak identification in the model ( $p=0.0000$; $\mathrm{F}=105.16>19.93$ ) and was unable to reject the null hypothesis in a test for possible overriding restrictions ( $p=0.2876$ ). Thus, the relevance and validity of the instruments, and hence their use in the supplementary instrumental variable model, was supported. Moreover, testing revealed that the bias in the original (RE) estimates was significantly large and thus warranted mitigation through the use of an IV model - employing the URG and UDG cost weights.

With regard to the control variables, the impact of clinical urgency depends on two factors: (i) patient severity (more urgent patients are given priority and thus have lower individual waiting times), and (ii) assessment and treatment time which can affect waiting time for other patients. Thus, whilst triage 1 and 3 patients had relatively low individual waiting times, they typically require lengthy treatments and greater staff attention, raising
waiting times for other patients and hence the median waiting time. Conversely triage 4 and 5 patients - which are generally associated with lower treatment times - typically endure higher individual waiting times. For triage 4, the lower assessment and treatment time dominates, resulting in a negative association with median waiting time, whilst for triage 5 the higher individual waiting time dominates, creating a positive association. This result is consistent with previous evidence in the literature [22,23].

In terms of human resources, it is somewhat unsurprisingly to find that employing additional nurses and medical officers lowers the median waiting time, ceteris paribus. However, additional administration staff (holding numbers of medical staff constant), are associated with increased median waiting times. Given hospital budgets are largely fixed, this may be a result of directing resources away from medical activities in favour of administrative functions.

The size of the LHNs also has a significant effect. Compared to medium size LHNs (the reference category), large or very large LHNs are associated with significantly longer median waiting times. This is likely because these LHNs provide treatment to more complicated cases (commonly referred to them by smaller LHNs), that might be expected to consume considerable resources, increasing congestion and thus giving rise to longer waits for other patients [1].

For the community demographic and health risk factors, once patient severity is controlled for there is little evidence of statistically significant associations [1]. The exception is the percentage of overweight or obese individuals, where a significant positive association with median waiting time is found. One potential explanation is that overweight and obese patients can require additional or specialised resources for treatment which may take additional time to procure and operate. Examples include additional staff for transportation, or medical equipment designed for patients with higher body weights such as stretchers, beds, wheelchairs or blood pressure cuffs [24]. Moreover, even for identical procedures (such as measuring vital signs) it has been recognised that a longer time is often required for overweight and obese patients [25].

Similarly, when the severity of the patients was accounted for, the year dummies and season weights were statistically insignificant. The exception is the 2016 year, which was statistically higher in certain models. One possible explanation may be the occurrence of a demand shock (an epidemic thunderstorm asthma event) during this period [26].

Table 3
Impact of Grant Funding on the Percentage of Patients Seen on Time, Victorian LHNs, 2015-2018.

|  | Model 3 (All Triage) | Model 4 (Tri2) | Model 5 (Tri3) | Model 6 (Tri4) | Model 7 (Tri5) |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Target | n.a. | Within 10 minutes | Within 30 minutes | Within 60 minutes | Within 120 minutes |
| Total Grant (\$10,000 s) | 0.469** (0.162) | 0.482** (0.187) | 0.610** (0.186) | 0.357* (0.174) | 0.243* (0.098) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| N | 88 | 88 | 88 | 88 | 88 |
| Coefficient of Determination | 0.7646 | 0.6606 | 0.7998 | 0.7400 | 0.7292 |

Robust standard errors in parentheses.
${ }^{+} \mathrm{p}<0.10$.

* $\mathrm{p}<0.05$.
** $\mathrm{p}<0.01$.

With regard to the principle variable of interest - grant funding - a highly significant negative association was identified. That is, higher levels of grant funding are associated with lower median wait times, after controlling for LHN, patient, and community characteristics. Moreover, regardless of the model employed (random-effects or IV), the coefficient for grant funding remained highly significant and negative in both models, supporting the robustness of the results obtained.

Given the size of the coefficient in the IV model, an additional $\$ 10,000$ in grant funding might be expected to lower the median wait time by approximately 2.3 min on average, ceteris paribus. This is likely because additional funding might enable hospitals to increase their available supply of treatment, through the procurement of more specialised or experienced staff, more advanced procedural or information technology systems, and additional equipment [9]. Thus, the results suggest that federal or state governments might play an important role in reducing waiting times through the provision of higher levels of funding.

However, while the results indicate that funding can improve waiting times, they can only provide limited support for policymakers in determining an optimal grant quantums. To overcome this limitation a suitable target is needed, and the clinically recommended waiting time targets which have been advocated by policymakers and included as a priority for LHNs represent a promising avenue [16]. Consequently, we have expanded our initial analysis to examine the effect of funding on the percentage of patients seen within clinically recommended waiting times (see Table 3; full results in Table A3). As endogeneity was not found to exist in these supplementary models ( $p>0.05$ for all models), IV estimation was not required. Whilst Model 3 includes the overall percentage of patients seen on time, Models 4-7 disaggregates this into individual triage categories (excluding triage 1 where all patients were seen immediately). It is important to note that the coefficients of these Models (3-7) have opposing signs to the earlier Models (1-2) because higher waiting times generally lead to less patients being seen on time.

In this model a positive coefficient was observed, indicating that higher levels of funding are associated with higher percentages of patients being seen on time ( 0.469 percentage points higher for every $\$ 10,000$ in additional funding), ceteris paribus. While the effect on individual triages varied (ranging from 0.243 to 0.610 percentage points), the results remained significantly positive. Thus, it is reasonable to conclude that additional funding might ensure more LHNs meet the clinically recommended targets.

These results provide useful guidance for policymakers in determining the precise quantum of funding required. However, some caution should be exercised given that the marginal effect of additional funding might diminish (that is the effect which additional funding has on waiting times and the proportion of patients seen on time might decrease as the magnitude of funding increases). Nevertheless, given the substantial cost of alternative projects to reduce waiting times and achieve clinical targets (such as the construction
of a new $\$ 1.5$ billion hospital at Footscray [27]) additional funding potentially presents a more cost-effective solution, providing better value for taxpayers.

## 3. Discussion

As our results suggest, increased government funding may be an effective solution to address excessive waiting times. However, as scholars such Sivey (2018) [2] have identified, simply targeting waiting time reductions through increased supply may not be sufficient. This is because lower waiting times may actually result in greater numbers of patients seeking treatment (most notably from walkouts). To avoid a return to higher waiting times, demand for treatment must also be targeted. One possible avenue, suggested by the statistically significant association in our regressions, is the reduction of obesity in the community.

For governments, there is a role in supporting obesity reduction through 'health promotion' and 'disease prevention' activities. The former - health promotion - includes public awareness campaigns to increase health literacy [5], and policies to encourage healthy lifestyles or active forms of transport (i.e. walking or cycling) [28]. Conversely, the latter - disease prevention - includes measures such as restrictively high taxes on unhealthy products (such as fast food and soft drinks), or restrictions to supply and advertisement of unhealthy products (particularly when directed towards children [5]). By applying such measures, it may be possible for governments to reduce the prevalence of obesity in the wider community, and potentially reduce the demand for emergency treatment stemming from obesity-related problems.

Thus, through targeting reductions to demand for emergency treatment, in addition to increased funding, it might be possible for governments to achieve reductions in waiting times over the short- and long-run.

## 4. Conclusion

The absence of a price mechanism often means that waiting times must act as a rationing device. Rising waiting times for emergency treatment have resulted in calls for additional government funding to enable investment in capacity. As our results indicate, increased funding has the potential to create statistically significant reductions in ED waiting time and increase the percentage of patients seen within clinically recommended time limits.

The next step for policymakers will be to determine the appropriate quantum of funding (given budget constraints), the optimal waiting time levels or targets, the desired funding instrument (e.g. block funding or in-kind support), and the LHNs which have the greatest need. Although these are primarily political decisions, to facilitate informed decision-making and provide tailored support, additional detailed econometric examination of individual LHNs or hospitals may be necessary. This should ensure that public funds
are used in the most efficacious manner to maximise the benefits obtained.

Consideration should also be given to the reduction of obesity in the wider community. We have outlined just a few possibilities above. Similarly, additional quantitative analysis (such as regression modelling and cost-benefit analysis) might be required to model the effects of potential policy instruments to target obesity, as well as the resources necessary for implementation, in order to select the most suitable approach.

Finally, the replication of this research on an inter-jurisdictional or international basis might prove fruitful. This will indicate whether the results and policy recommendations proposed above can be readily applied to other health systems, or if the significant differences in healthcare and waiting time management systems, both nationally and internationally, necessitate a different approach [29].

To improve the waiting time for emergency treatment and ensure that patients are able to access health interventions in a timely manner, a unified effort by medical professionals, LHNs, governments and scholars alike is needed.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.healthpol.2020. 09.008.

## Declaration of Competing Interest

The authors report no declarations of interest.

## References

[1] Johar M, Savage E, Stavrunova O, Jones G, Keane M. Geographic differences in hospital waiting times. The Economic Record 2012;88(281):165-81.
[2] Sivey P. Should I stay or should I go? Hospital emergency department waiting times and demand. Health Economics 2018;27(3):e30-42.
[3] Gaughan J, Kasteridis P, Mason A, Street A. Why are there long waits at English emergency departments? European Journal of Health Economics 2020;21(2):209-18.
[4] Sivey P, McAllister R, Vally H, Burgess A, Kelly A. Anatomy of a demand shock: quantitative analysis of crowding in hospital emergency departments in Victoria, Australia during the 2009 influenza pandemic. PLoS One 2019;14(9):e0222851.
[5] Australian Institute of Health and Welfare (AIHW). Australia's Health. Australia's health series no. 16. AUS 221. Canberra: AIHW; 2018.
[6] Martin S, Rice N, Jacobs R, Smith P. The market for elective surgery: joint estimation of supply and demand. Journal of Health Economics 2007;26(2):263-85.
[7] Pines J, Hilton J, Weber E, Alkemade A, et al. International perspectives on emergency department crowding. Academic Emergency Medicine 2011;18(12):1358-70.
[8] Harriss L, Thompson F, Lawson K, O'Loughlin M, McDermott R. Preventable hospitalisations in regional Queensland: potential for primary health? Australian Health Review 2019;43:371-81.
[9] Australian Medical Association (AMA). Public hospital report card: an AMA analysis of Australia's public hospital system; 2019.
[10] Shorten B, 2019, May 5th Australian federal election speeches. Parkes, Australia: Museum of Australian Democracy (MOAD); 2019.
[11] Stephens A, Broome R. Impact of emergency department occupancy on waiting times, rates of admission and representation, and length of stay when hospitalised: a data linkage study. Emergency Medicine Australasia 2018;31(4):555-61.
[12] Xu Y, Ho V. Freestanding emergency departments in Texas do not alleviate congestion in hospital-based emergency departments. The American Journal of Emergency Medicine 2020;38(3):471-6.
[13] Myers M, Sheehan K. The impact of certificate of need laws on emergency department wait times. The Journal of Private Enterprise 2020;35(1):59-75.
[14] Tabriz A, Trogdon J, Fried B. Association between adopting emergency department crowding interventions and emergency departments' core performance measures. American Journal of Emergency Medicine 2020;38:258-65.
[15] Chen Y, Meinecke J, Sivey P. A theory of waiting time reporting and quality signaling. Health Economics 2015;25(11):1355-71.
[16] Department of Health and Human Services (DHHS). 2019-20 statement of priorities. Melbourne, Australia; 2020.
[17] Independent Hospital Pricing Authority (IHPA). Consultation paper on the pricing framework for Australian public hospital services 2018-19. Sydney, Australia; 2017.
[18] Johar M, Jones G, Savage E. Emergency admissions and elective surgery waiting times. Health Economics 2013;22:749-56.
[19] Naiker U, FitzGerald G, Dulhunty J, Rosemann M. Time to wait: a systematic review of strategies that affect out-patient waiting times. Australian Health Review 2018;42:286-93.
[20] Australian Institute of Health and Welfare (AIHW). MyHospitals [Database]. Canberra: AIHW; 2018 https://www.myhospitals.gov.au/about-the-data/ download-data.
[21] Australian Bureau of Statistics (ABS). Data by region 2013-2018. ABS cat. 1410.0. Canberra, Australia; 2019 https://www.abs.gov.au/ausstats/abs@.nsf/mf/1410. 0.
[22] Elkum N, Fahim M, Shoukri M, Al Madouj A. Which patients wait longer to be seen and when? A waiting time study in the emergency department. EMHJ Eastern Mediterranean Health Journal 2009;15(2):416-24.
[23] Canadian Institute of Health Information (CIHI). Health care in Canada 2012: a focus on wait times. Ottawa, Canada; 2012.
[24] Singh N, Arthur H, Worster A, Iacobellis G, Sharma A. Emergency department equipment for obese patients: perceptions of adequacy. Journal of Advanced Nursing 2007;59(2):140-5.
[25] Bambi S, Dettori I, Ruggeri M. Morbidly obese patients in emergency department: are we ready to face the challenge. European Journal of Emergency Medicine 2013;20(4):293-4.
[26] Department of Health and Human Services (DHHS). The November 2016 Victorian epidemic thunderstorm asthma event: an assessment of the health impacts. Melbourne, Australia; 2017.
[27] Mikakos J. Building the best hospitals for Victorian patients. Minister for Health and Ambulance Services, Government of Victoria; 2019.
[28] Swinburn B. Obesity prevention: the role of policies, laws and regulations. Australia \& New Zealand Health Policy 2008;5(12), http://dx.doi.org/10.1186/ 1743-8462-5-12.
[29] Viberg N, Forsberg B, Borowitz M, Molin R. International comparisons of waiting times in health care- Limitations and prospects. Health Policy 2013;112(1-2):53-61.


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