Do mergers benefit patients in underperforming administrations? Lessons from Area Health Service Amalgamation

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Abstract

Evidence supporting the effects of mergers in health care markets on quality is mixed. In this study we exploit a government policy in NSW that imposed mergers on area health services (AHS) to evaluate the effects of the merger on patient waiting times, an indicator of quality. We focus on the specific question of whether the merger had a larger impact on less-well performing AHSs. Our results show heterogeneous impacts, reducing waiting times for relatively urgent public patients but further delaying non urgent patients. In addition, we find the merger reduced the waiting time gap between public and private patients.

JEL Codes I1, H4

Keywords hospital waiting times, administrative mergers, equity

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I. Introduction

Faced with increasingly tight health budgets, entities in many health markets reorganize to improve efficiency. There have been consolidations of hospitals, private health insurers, HMOs, local health networks and primary care providers (see Shaw 2003; Cuellar and Gertler 2003). One outcome of consolidation can be a reduction in the quality of care for patients in some or all of the entities involved. Consolidation may even adversely affect access to care to potential patients (Hammer and Sage, 2003). Others focus on law and regulations and the predictors of merger or acquisition (see Feldman et al. 1996; Town et al 2007) or the impact of the consolidation on prices (see Connor et al 1997; Town et al 2006). Other studies examining the impact of the consolidation on measures of quality of care have been based on hospital mergers and mortality among the hospitalized population (Hayford, 2012; Gaynor and Town, 2013). In general, these studies find that hospital mergers improve quality. However this conclusion is often based on a single, or a small number of hospitals, or relies on the management of specific conditions, such as heart attack, or patients at the end of their lives, so it may not generalize to the wider population. In addition, most of this empirical evidence comes from private hospitals in the US which has a very distinctive health system. Gaynor et al (2012), Azevedo and Mateus (2013) and Bloom et al (2013) are among the few studies that have analyzed the impacts of hospital mergers in public systems.[1] The results are mixed. In the UK, Gaynor et al (2012) do not find that merger increases quality (measured by death rates from emergency heart attack (AMI) admissions and length of stay) while Bloom et al (2013) find a positive merger impact on management quality. In Portugal, Azevedo and Mateus (2013) find that instead of lowering costs, post-merger costs are higher.

To credibly estimate the impacts of a merger is challenging because the entities which choose to merge have distinctly different characteristics compared with the non-merging entities. Although some of these characteristics can be observed, some others may not, creating selection bias when we compare, for example, the health outcomes of patients or consumers of merging and non-merging entities. If the merging entities also tend to be those which provide high quality of care, then we may misleadingly attribute better care to the merger. It is also possible that the true effect of the merger is negative but it is counteracted by the positive effect of the inherent features of the merging entities on quality of care. If a merger can be randomly imposed on entities, then we

[1] Related studies that look at the impact of competition per se (e.g., variation in hospital concentration across areas or increased choice of hospital) include Propper et al (2008), Propper et al (2004), Gaynor et al (2011) and Cooper et al (2011).

do not have to worry about selection bias. However, there are few real-life experiments involving randomized mergers.

In this study, we exploit a government policy in New South Wales (NSW) in 2005 that imposed mergers on pairs (or trios in some cases) of adjacent area health services (AHS) to examine how a merger in the health sector may have impacted quality of care. Figure 1 illustrates the amalgamation of the 17 AHSs in NSW to 8 larger AHSs; the dark thick lines show the AHS boundaries after the amalgamation. As the measure of quality we use patient waiting times for non-emergency or elective surgeries. Longer waiting times not only cause prolonged suffering to patients (Oudhoff et al, 2007; Hodge et al, 2007), but may also indicate inefficiency and administrative weaknesses of the health system (Siciliani et al 2013). In settings where elective surgeries are provided free of charge, demand is rationed by waiting times, prioritized by urgency. In Australia there are three categories of urgency: *urgent* to be admitted within 30 days, *semi-urgent* within 90 days and *non-urgent* within 365 days.

[Insert Figure 1]

The amalgamation aimed to significantly reduce administrative costs, which had grown by over 50% in 5 years. Before the merge each AHS acted like a private entity, governed by a Health Board and run by a Chief Executive Officer. After the merger, the Health Boards were dissolved and replaced with a

Health Advisory Council made up of clinicians and community representatives. They were charged with achieving an allocation of health resources more aligned with the needs of the community. The AHS amalgamation was expected to improve equity through redistribution of health workforce and also to improve the image of the overall NSW health system that had often been criticized for delivering poor quality health care, indicated in particular by long waiting times for free elective surgery in public hospitals.

The amalgamation affects all AHSs in NSW so we focus on the specific question of whether the AHS amalgamation had a larger impact on less-well performing AHSs prior to the merger. We contribute to existing knowledge of the link between quality and merger in the health sector in four significant ways: (1) as the amalgamation is forced, our setting avoids selection biases associated with voluntary mergers; (2) we use a patient health-related outcome that is not restricted to a particular hospital or disease; (3) we explore the merger effects over time; and (4) we investigate possibly heterogeneous impacts of the merger on equity of access related to patient payment status.

II. Data and methods

NSW has over half a million hospital admissions annually from waiting lists. Our data is derived from the Waiting List Data Collection database consisting of all admissions from waiting lists to NSW public hospitals from July 2004 to December 2010. At the start of the study period, there were 108 public hospitals in the data, and this number remains roughly the same by the end of the study period. We focus on patients who were NSW residents and were not admitted with special group status such as Veteran's Affair or Workers' Compensation (3.1%). We have 1,735,715 observations. The mean patient age is 52 and 53% are female. The outcome variable, waiting time, is defined as the time between being placed on the waiting list by a treating specialist and admission to hospital.

Within a merged pair we define the "underperformer" as the AHS with longer average waiting time before the amalgamation within their respective pair. Figure 2 shows the distribution of the pre-merger waiting time in each of the 8 amalgamated AHS pairs. Pairs 3, 5 and 8 involve the amalgamation of 3 AHSs. In pair 1, AHS B (dashed line) has many more cases of patients waiting longer than 100 days than AHS A, resulting in longer average waiting time. So, for pair 1, AHS B is the underperformer. Likewise, AHS B is the underperformer in pairs 3 to 6, AHS A is the underperformer in pairs 2 and 7 and AHS C is the underperformer in pair 8.

[Insert Figure 2]

To estimate the impact of the amalgamation, we take advantage of the panel nature of the data to compare waiting times in the under performing and better performing AHSs, taking into account differences between them before the merger. Because the underperformers initially have longer average waiting time, a positive merger effect arises from convergence towards the better performers' waiting time or an even shorter waiting time than that of the better performing AHSs. Because we observe these AHSs for quite a number of years post treatment, we can study the time path of the merger effect.

Specifically, we estimate the following equation:

$$y_{it} = \alpha T_t + \beta(D_{it} \times T_t) + \delta X_{it} + \varepsilon_{it},$$

where $\mathbf{y_{it}}$ is the waiting time of patient $\mathbf{i\,(i = 1, \ldots, N)}$ in time $\mathbf{t\,(t = 0, \ldots 6)}$, $\mathbf{T}$ is a vector of dummy variables for year, T_0 is the pre-merger period, $\mathbf{D}$ is a dummy variable for underperformers, $\mathbf{X}$ is a vector of age, sex, procedure and hospital peer group fixed effects, and $\boldsymbol{\varepsilon}$ is a random error term. The use of year dummies allows the merger effects to vary over time. Non-linear trend effects may arise from short-run adjustment constraints or administrative diseconomies of scale in later years. The addition of the $\mathbf{X}$ vector controls for changes in severity of patients or case mix over time, as well as hospital peer effects.

We estimate the model using Ordinary Least Square (OLS) separately for urgent, semi-urgent and non-urgent urgency admissions.[2] This conditioning accounts for the fact that some procedures are more likely to be assigned to one urgency category than others (e.g., cardiac catheterization is almost never assigned to the non-urgent category). In addition, we distinguish paying (or private) patients from public patients. In NSW public hospitals, patients can be admitted as public or private patients. Public patients are treated without charge whilst private patients incur hospital and medical charges in exchange for choice of doctor and possibly a better standard of accommodation. The revenue that a public hospital receives from admitting private patients is additional to the (fixed) revenue derived from government payments. As well, private patients are a source of fees for the treating specialists, giving incentives for hospitals and specialists to expedite private patient admissions in public hospitals (Johar and Savage 2012). The share of private patients is lower in underperforming AHSs, about 7%, than in the better performing AHSs, about 20%, but we find that these shares remain stable over the study period, suggesting that the AHS mergers had little impact on the mix of paying and non-paying patients in public hospitals. The standard errors of estimates are

[2] Waiting times have a long right tail. By conditioning on urgency categories, the waiting time distribution is more normally distributed around the conditional (on urgency category) mean. OLS on the true scale is preferred to a logarithmic transformation because of problems with re-transformation, interpretation and inference.

clustered at the hospital-level to account for correlation between patients within a hospital.

We conduct several sensitivity tests. The first test concerns the use of the median or the proportion of waiting beyond the recommended time, rather than the average, to define underperformers. Both alternative measures change the definition of the underperforming AHS in only 1 of the 8 pairings. The second test concerns the sensitivity of the results to time of year. We explore this by restricting the data to only the second half of each year. Third, we test the merger effect against a related policy change at around the same time. One year after the AHS amalgamation, the NSW Department of Health released the *Advice for Referring & Treating Doctors - Managing Elective Patients/ Waiting Lists*, which contains recommendations for doctors in assigning the urgency category for 164 elective procedures.[3] The guideline is not mandatory. We can use this to test the merger effect because, while the AHS amalgamation affects all patients, only those undergoing the selected procedures are covered by the guideline. We test for the merger effect within the subsample of procedures that are not covered by the guideline.

[3] The guideline, released in April 2006, assigned selected procedures to at least one urgency category. We use the subset 138 procedures for which there is only one urgency category. http://www.health.nsw.gov.au/policies/pd/2006/pdf/PD2006_020.pdf

III. Results

First, in Figure 3 we plot the unconditional (raw) mean waiting times before (time 0) and after the AHS amalgamation by urgency category. It shows that in all urgency categories private patients have much shorter waiting times than public patients. As expected, at time = 0, waiting times are substantially longer for underperformers, especially for public patients. Post-merger, waiting times for urgent and semi-urgent public patients in underperforming AHSs reduce sharply, whilst the waiting times of private patients generally increase. Regardless of payment status, non-urgent patients experienced longer delays in being admitted.

[Insert Figure 3]

Table 1 reports the effect of the merger, controlling for differences in other patient and hospital characteristics.[4] Starting with the waiting time of the most urgent patients, we find a positive merger effect only for public patients. Pre-merger public patients in underperforming AHSs wait 12.5 days longer than their counterparts but after three years, this gap narrows to 2 days and subsequently disappears. The same cannot be said for private urgent patients. Initially, they wait about the same time but post-merger private patients in underperforming AHSs wait 3-6 days longer than their private

[4] Because there are hundreds of covariates, for conciseness we do not report the estimates of δ.

counterparts. For semi-urgent patients, the merger also benefits public patients. By the end of the study period, the merger had eliminated the public waiting time gap between AHSs which had been over 30 days pre-merger. In contrast, for semi-urgent private patients in underperforming AHSs, although there is a small reduction in the waiting time gap, by six years post-merger they still wait 20 days longer than their counterparts in better performing AHSs. Finally for the non-urgent patients, the merger had unfavourable impacts on both public and private patients. In the last two years of the study period, admissions of non-urgent public patients in underperforming AHSs were delayed by over 40 days compared with their counterparts in the better performing AHSs, and for non-urgent private patients, this gap is 90 days.

[Insert Table 1]

In Table 2 we present results from the sensitivity analyses split by public and private patients. The sizes of the merger effects vary from those in Table 1 but they show a consistent pattern., Column [1] uses the alternative definition of underperformers (median or proportion of overdue admissions). Either modification affects only one AHS pair so it is not surprising that the results are very close to those in Table 1. Column [2] uses only admissions in the second half of each year. The results confirm that our main results are not driven by within-year demand fluctuations in admissions. Results presented in Column [3] use only patients whose procedures are unaffected by the contemporaneous release of the NSW clinical priority guideline, which may otherwise confound the merger effect. They show estimated merger effects that are quite close to those in Table 1 suggesting that our main results are not driven by the guideline policy.

[Insert Table 2]

IV. Discussion

Our results show that following merger, the merged entities re-prioritized, producing heterogeneous impacts. Specifically, it improved access for relatively urgent (urgent and semi-urgent) public patients, who make up 60% of all admissions, and it also had equity implications, reducing the waiting time gap between public and private patients. While the waiting time gaps for urgent and semi-urgent public patients dramatically diminish, their private counterparts experience an increase in waiting time gap or a small reduction in waiting time gap. As suggested by Figure 3, this contrasting pattern implies a convergence of the waiting times of urgent and semi-urgent public patients to those of their private patient counterparts. In addition, post-merger delays in non-urgent admissions are larger for private patients which imply a convergence of the non-urgent public and private patients’ waiting times as well. As improved equity was one of the goals of the amalgamation, this is a positive result.

We find that the positive merger effects were achieved in a relatively short period (2-3 years). To determine that the positive merger effects are not driven by patients leaving public waiting lists, we check throughput over the period. Table 3 shows that, for both public and private patients, throughput has stayed largely stable, suggesting that the merger did not discourage demand for elective procedures in public hospitals. The public-patient share also remains stable over time, suggesting that private patients did not leave the public sector due to longer waiting times.

[Insert Table 3]

Our analysis suggests that the majority of patients were better off as a result of the merger. Although non-urgent patients, who already faced long waiting periods, were further delayed and private patients lost their advantage, for the bulk of those who were made worse off, waiting times remained within the recommended clinical time.

A relevant question is how the re-prioritization occurred? The assignment of urgency category is clearly one of the main mechanisms to influence waiting times. In the absence of a formal or mandatory prioritization rule (Curtis et al 2010), providers can manipulate urgency assignment. For example, treating specialists can expedite admissions by assigning patients to a higher urgency category. This problem may be exacerbated by policies that target urgent admissions, notably the federal government's Elective Surgery Waiting List Reduction Plan (ESWLRP)[5] announced in 2008. The plan provided funding increases to states that achieved certain performance measures, one being a reduction in overdue admissions (i.e., those exceeding the recommended waiting time). Such a policy may encourage assignments to less urgent categories because target admission periods are longer. This may provide an incentive for underperformers to manipulate the urgency assignment to a larger extent than others.

To investigate this, we estimate a multinomial logit of urgency category and report the risk ratios of an assignment to a less urgent category relative to the assignment to the most urgent category. Table 4 reports the relative risk ratios of the time trends and their interactions with the indicator variable for underperformers. The time trends pick up an increasing number of both public and private patients being assigned as less urgent over time but there is lack of evidence that the underperformers are doing it more. The results in Table 4 also suggest that the waiting time improvement in Table 1 for underperformers arises from better administrative and management systems, rather than being driven by a manipulative behaviour of health providers to

[5] http://www.federalfinancialrelations.gov.au/content/npa/health_infrastructure/elective_surgery/national_partnership.pdf

attract additional funding. For private patients in underperforming AHSs, the merger actually decreased the probability of being assigned to less urgent categories, which may partly explain the increased waiting time gap for urgent private patients (Table 1).

[Insert Table 4]

Our finding of heterogeneous merger impacts highlights the importance of going beyond evaluating a policy by the overall impact, which can mask large effects in opposite directions as is the case here. The next lesson from our results is that a positive shock to a system can bring about an immediate large improvement. This is perhaps why entities merge in the first place, to “fix things”. While making a convincing statement about long-run effects of a merger is beyond the scope of this paper, our results do suggest that mergers can result in sustained improvements for some years. By restructuring administration, mergers can interrupt the routine practices of the previous system. In our case, this is illustrated by the diminishing preferential treatment of paying patients on the waiting lists. The equity implication of the result is compelling. Opponents of mergers have argued that mergers increase inequity, for example through adverse selection (Town et al 2007).

A widespread view among health policymakers is that mergers often harm consumers by raising prices without producing an accompanying increase in quality (Cuellar and Gertler 2005). Overall, our results indicate that mergers in the health sector can improve quality and equity.

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Table 1: The effect of AHS amalgamation on waiting time

	Public						Private					
	Urgent		Semi-urgent		Non-urgent		Urgent		Semi-urgent		Non-urgent	
	b	se	b	se	b	se	b	se	b	se	b	se
T 1	1.937***	(0.583)	8.341***	(2.486)	16.967**	(6.749)	-0.087	(0.653)	3.352*	(1.955)	3.12	(3.902)
T 2	-0.279	(1.075)	3.823	(2.736)	-15.194*	(8.698)	-2.345**	(1.178)	1.726	(2.466)	-6.689	(6.048)
T 3	-6.156***	(1.342)	-4.259	(3.882)	-27.310**	(10.710)	-4.650***	(1.437)	-0.764	(2.418)	-7.159	(4.744)
T 4	-7.590***	(1.474)	-7.645**	(3.836)	-16.810*	(10.057)	-4.934***	(1.338)	-1.083	(2.827)	-4.688	(5.030)
T 5	-6.739***	(1.459)	-13.456***	(4.619)	-6.883	(9.912)	-4.517***	(1.265)	-2.282	(3.002)	-2.199	(6.436)
T 6	-6.394***	(1.367)	-12.634***	(4.650)	14.293	(10.535)	-4.291***	(1.495)	-0.968	(3.115)	9.195	(7.908)
D x T 0	12.473***	(3.785)	34.232***	(8.099)	23.334	(17.087)	2.168	(2.353)	27.572***	(9.155)	15.085*	(7.865)
D x T 1	12.352***	(4.096)	36.456***	(9.051)	35.384**	(14.781)	1.329	(2.009)	10.645	(7.672)	6.004	(8.318)
D x T 2	6.271**	(2.992)	25.912***	(6.472)	25.933**	(12.141)	4.101**	(1.713)	17.184***	(4.557)	5.686	(7.701)
D x T 3	1.964**	(0.989)	16.916***	(5.682)	27.629**	(12.271)	2.988***	(0.928)	14.942***	(4.247)	34.165***	(9.256)
D x T 4	1.19	(0.968)	15.019***	(5.407)	27.380**	(11.683)	3.263***	(0.756)	20.031***	(5.353)	42.266***	(10.502)
D x T 5	0.931	(1.188)	8.718*	(4.997)	40.395***	(12.447)	4.611***	(1.636)	19.446***	(5.329)	85.820***	(18.168)
D x T 6	0.934	(1.447)	7.436	(4.812)	44.917***	(14.110)	5.916***	(2.012)	22.104***	(7.158)	89.567***	(15.957)
N	556,770		488,948		458,532		121,485		66,579		43,401	
R-squared	0.144		0.128		0.209		0.106		0.0931		0.148	

Note: these results are based on linear regression separately for each urgency status. Included in the model are controls for patient demographics, procedures and hospital peer. Standard errors are clustered at hospital-level. *, ** and *** denotes statistical significance at 10%, 5% and 1%, respectively. The p-values for F-statistics under the null of all coefficients are zero are 0 in all models.

Table 2: Sensitivity analyses

	Public						Private					
	[1]		[2]		[3]		[1]		[2]		[3]	
	Median		Half year		Procedure		Median		Half year		Procedure	
	b	se	b	se	b	se	b	se	b	se	b	se
Urgent												
D x T 0	12.848***	(3.735)	12.571***	(3.840)	10.624**	(4.072)	2.431	(2.295)	2.209	(2.365)	1.833	(2.393)
D x T 1	12.915***	(4.016)	11.214***	(3.628)	9.399**	(4.123)	3.016	(2.180)	2.4	(2.415)	1.368	(2.356)
D x T 2	6.155**	(2.953)	4.741**	(2.334)	4.265	(2.820)	4.146**	(1.700)	2.731*	(1.496)	3.892**	(1.857)
D x T 3	1.634*	(0.969)	0.845	(0.843)	0.788	(1.028)	3.363***	(0.932)	2.885***	(0.901)	3.330***	(1.244)
D x T 4	1.043	(0.846)	0.965	(0.984)	0.165	(1.030)	3.891***	(0.753)	3.102***	(0.793)	3.799***	(0.987)
D x T 5	0.573	(1.033)	1.112	(1.166)	0.414	(1.283)	5.047***	(1.527)	3.739***	(1.157)	4.815**	(1.918)
D x T 6	0.677	(1.301)	1.163	(1.508)	0.024	(1.728)	6.080***	(1.831)	6.535***	(2.348)	4.757***	(1.535)
Semi-urgent												
D x T 0	33.863***	(8.213)	34.373***	(8.131)	34.705***	(9.085)	17.811***	(6.458)	27.385***	(9.235)	28.218*	(15.007)
D x T 1	37.010***	(8.978)	34.482***	(9.081)	34.493***	(9.162)	20.897***	(7.479)	5.247	(7.214)	7.816	(9.601)
D x T 2	25.289***	(6.413)	24.713***	(6.089)	24.858***	(6.797)	21.516***	(4.442)	17.596***	(4.705)	18.448***	(6.092)
D x T 3	15.493***	(5.631)	15.405***	(5.815)	16.736***	(5.360)	19.401***	(3.821)	16.378***	(4.369)	13.258***	(4.856)
D x T 4	13.872**	(5.454)	12.035**	(5.192)	13.757**	(5.379)	22.151***	(5.426)	15.995***	(5.210)	17.252***	(5.548)
D x T 5	7.578	(4.631)	8.987*	(4.974)	9.938*	(5.083)	22.721***	(5.740)	21.046***	(6.237)	20.436***	(5.910)
D x T 6	8.113*	(4.735)	6.934	(4.467)	6.553	(5.339)	24.873***	(6.603)	21.435***	(7.780)	21.134**	(8.372)
Non-urgent												
D x T 0	27.617	(16.768)	23.004	(17.130)	22.639	(14.902)	18.553*	(9.375)	14.661*	(7.842)	-6.532	(10.294)
D x T 1	27.124*	(14.539)	35.582**	(13.824)	27.12	(17.820)	9.339	(8.478)	13.791	(9.207)	-6.572	(9.136)
D x T 2	21.763*	(11.702)	27.915**	(11.712)	20.171*	(12.077)	15.838*	(9.237)	14.001*	(8.357)	-8.475	(7.804)
D x T 3	24.871**	(11.858)	26.465**	(12.750)	34.941***	(12.390)	34.150***	(8.746)	32.432***	(10.107)	28.104**	(12.750)
D x T 4	28.696**	(11.655)	26.119**	(11.951)	29.916**	(14.589)	48.968***	(11.175)	41.558***	(9.004)	34.245**	(14.668)
D x T 5	37.745***	(12.177)	44.604***	(13.148)	39.138**	(15.491)	79.700***	(20.336)	93.383***	(18.034)	89.281***	(27.229)
D x T 6	40.986***	(14.151)	48.240***	(15.081)	36.582*	(20.462)	82.735***	(17.089)	87.768***	(17.362)	78.892***	(26.421)

Note: these results are based on linear regression separately for each urgency status. Included in the model are controls for patient demographics, procedures and hospital peer. Standard errors are clustered at hospital-level. *, ** and *** denotes statistical significance at 10%, 5% and 1%, respectively. The p-values for F-statistics under the null of all coefficients are zero are 0 in all models.

Table 3: Throughput by AHS pairing

		Short AHS			Long AHS		
Time	Overall	Public	Private	Total	Public	Private	Total
0	141,868	83,170	16,786	99,956	39,434	2,478	41,912
1	280,711	161,892	31,375	193,267	82,156	5,288	87,444
2	271,119	154,401	28,902	183,303	82,268	5,548	87,816
3	262,639	151,095	29,660	180,755	76,216	5,668	81,884
4	261,833	150,415	29,313	179,728	76,069	6,036	82,105
5	249,654	143,490	28,834	172,324	71,731	5,599	77,330
6	267,924	153,512	30,281	183,793	78,432	5,699	84,131

Table 4: Relative risk ratios from multinomial logit model of urgency category

	Public		Private	
	b	se	b	se
Semi-urgent				
T 1	1.002	(0.058)	0.969	(0.102)
T 2	1.244*	(0.138)	1.299	(0.235)
T 3	1.728***	(0.220)	1.749***	(0.365)
T 4	1.884***	(0.293)	1.968***	(0.469)
T 5	1.780***	(0.294)	1.794**	(0.488)
T 6	1.854***	(0.304)	1.920**	(0.547)
D x T 0	0.906	(0.136)	1.117	(0.286)
D x T 1	0.931	(0.122)	1.074	(0.214)
D x T 2	0.888	(0.103)	0.691*	(0.132)
D x T 3	0.888	(0.083)	0.767*	(0.121)
D x T 4	0.947	(0.095)	0.733**	(0.113)
D x T 5	1.031	(0.111)	0.698	(0.167)
D x T 6	1.112	(0.126)	0.696*	(0.146)
Non-urgent				
T 1	0.968	(0.047)	0.913	(0.064)
T 2	1.464***	(0.168)	1.543**	(0.277)
T 3	2.391***	(0.355)	3.115***	(1.227)
T 4	2.600***	(0.373)	3.466***	(1.063)
T 5	3.066***	(0.474)	3.667***	(1.055)
T 6	3.120***	(0.501)	3.193***	(0.901)
D x T 0	1.271	(0.304)	2.092**	(0.673)
D x T 1	1.342	(0.294)	2.145**	(0.757)
D x T 2	1.013	(0.216)	1.254	(0.462)
D x T 3	0.883	(0.175)	0.653	(0.326)
D x T 4	1.222	(0.168)	0.600	(0.231)
D x T 5	1.240	(0.163)	0.486**	(0.163)
D x T 6	1.343**	(0.184)	0.597*	(0.180)

Note: these results are based on multinomial logit models separately for public and private patients. The reference group is urgent category. Standard errors are clustered at hospital-level. *, ** and *** denotes statistical significance at 10%, 5% and 1%, respectively. Included in the model are controls for patient demographics, procedures and hospital peer.

Figure 1: Area Health Services Amalgamation

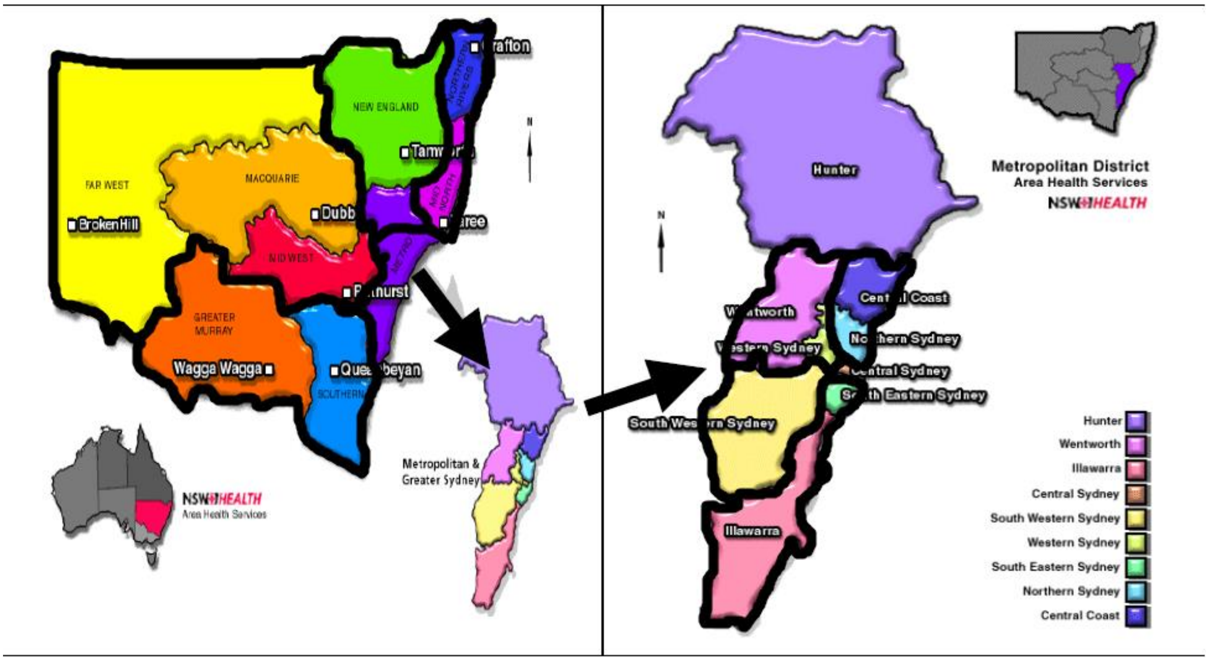
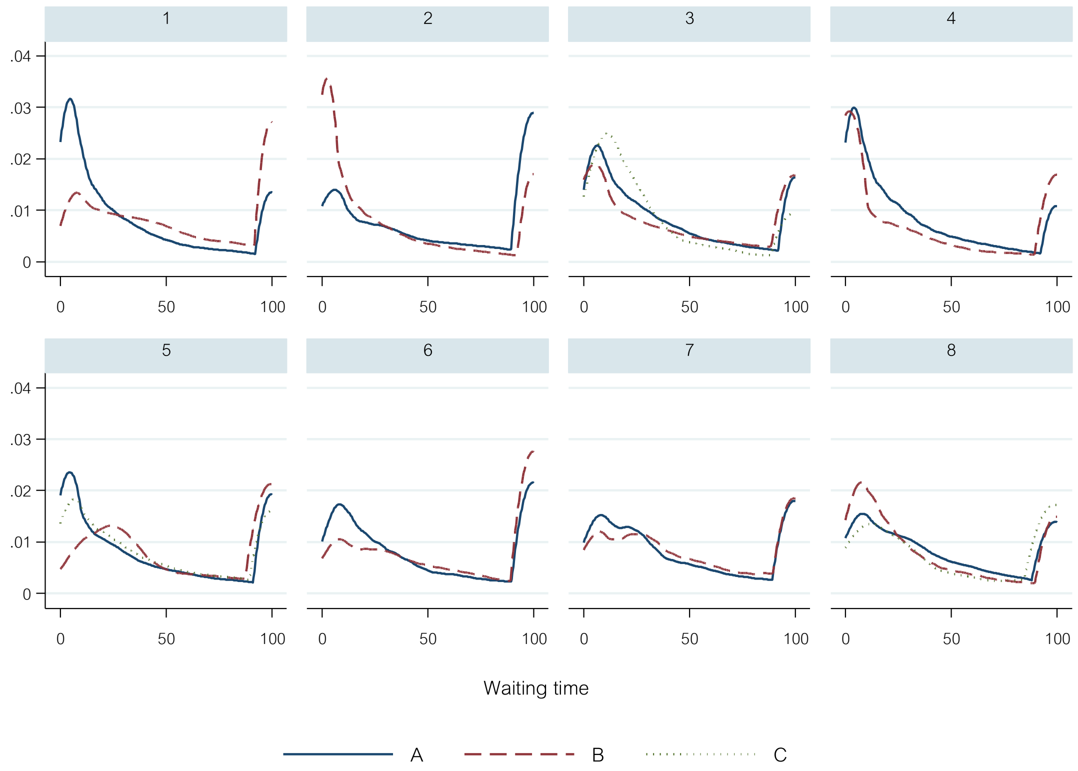
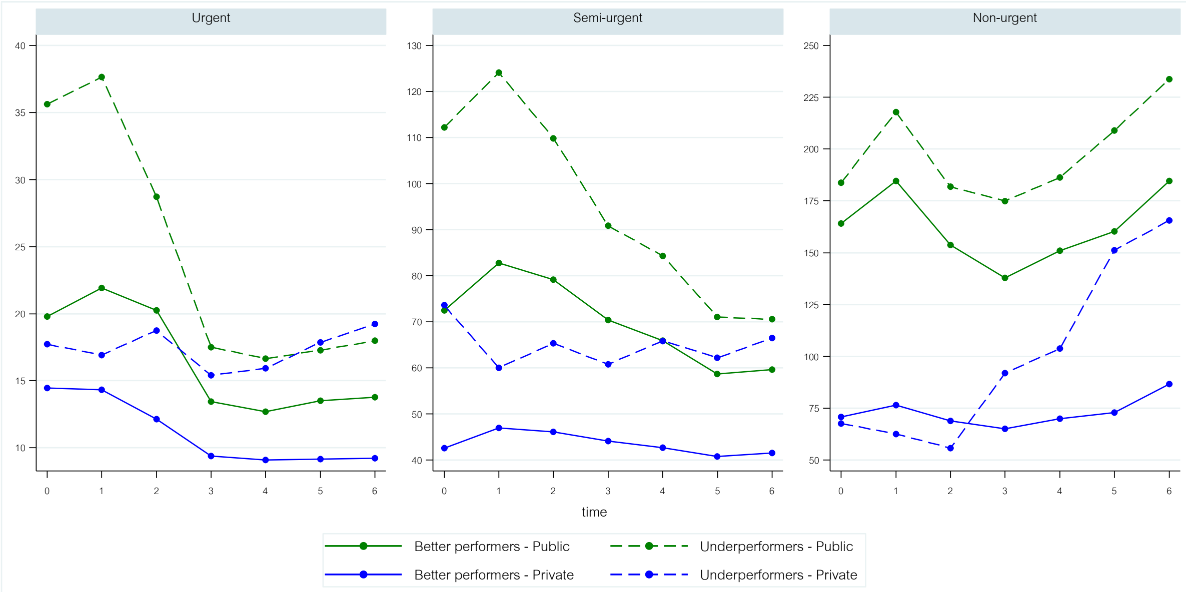


Figure 2: Distribution of waiting time prior to AHS amalgamation in each AHS pair



Note: waiting times beyond 100 days are top-coded to get a clearer picture of the distribution of the bulk of waiting time cases under 100 days. The sub-headings indicate the 8 AHS pairings after amalgamation. Each sub-graph plots the waiting time distribution in the original AHS (prior to pairing), differentiated by A, B and C, in the case where there are three merging AHSs.

Figure 3: Evolution of mean waiting time by patient and AHS status



Sources: Authors' analyses of the 2004-2010 Waiting List Data Collection data by NSW Health. The y-axis is waiting days and the x-axis is time. Time=0 is 2004, pre AHS amalgamation. Time= 1 to 6 indicates 6 years of post AHS amalgamation period.