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Abstract

The Australian government pays $6.5 billion per year in rebates to encourage Australians to purchase private health insurance (PHI) and an additional $3 billion to cover private inpatient medical services. What is the justification for large government subsidies to a private industry when all Australians already have free Medicare coverage? The government argues that more people buying PHI will relieve the burden on the public system and may reduce waiting times. However, the evidence supporting this is sparse.

We use an instrumental variable approach to study the causal effects of higher PHI takeup on waiting times in public hospitals. We use 2014-2018 hospital admission and elective surgery waiting list data linked at the patient level from the Victorian Centre for Data Linkage. These data cover all Victorian residents who had any inpatient admissions in all hospitals in Victoria (both public and private hospitals) and those registered on the waiting list for elective surgeries in public hospitals in Victoria. We find that one percentage point increase in the PHI take-up leads to about 0.34 days (or 0.5%) reduction in waiting times in public hospitals on average. The effects vary by surgical specialties and age groups. However, the practical significance of this effect is limited, if not negligible, despite its statistical significance.

The small effect suggests that raising PHI coverage with the aim to taking the pressure off the public system is not an effective and practical strategy in reducing waiting times in public hospitals. Alternative policies aiming at improving the efficiency of public hospitals and advancing equitable access to care should be a priority for policymakers.

JEL classification: I12, I13, I18, I51
Keywords: private health insurance, waiting time, public hospitals, Australia

1 Introduction

In countries with universal health insurance and minimal patient payments for public hospital services, non-urgent hospital treatment commonly has a waiting list in public hospitals. Some countries, e.g., the United Kingdom and Canada, manage waiting times by setting maximum wait targets, monitoring providers' performance, and providing sizable public funding (Willcox et al., 2007). Other countries (e.g., Australia) rely on a parallel private health sector to induce people to use more private hospital care, and thereby relieve the pressure on the public system.

This study examines whether the average waiting times in public hospitals change in response to the variation in private health insurance (PHI) enrollment in Australia.

Australia has a universal health insurance coverage, Medicare, which covers free care in public hospitals. In addition, the Australian government implements several interventions to support a parallel private system. The government subsidises A$6.5 billion per year in insurance premium rebates to encourage individuals to purchase PHI, and directly subsidises inpatient medical services in private hospitals by about A$3 billion a year (Duckett and Nemet, 2019). In addition, the government implements age-based penalty to encourage individuals to enroll in PHI earlier in life and tax penalty for those who do not have PHI if their income is above a certain threshold. What is the justification for large government subsidies and interventions to a private industry when all Australians already have universal health insurance coverage? The argument to support government subsidies and interventions for PHI is that patients using private care may substitute for public care and hence relieve the burden on the public hospital system, thereby reducing waiting times in public hospitals. However, the evidence supporting this argument is scant.

Causal analysis of the relationship between PHI and waiting time is an under-studied area for several reasons. Data on waiting times are difficult to obtain and complex to

interpret. Measures of waiting times across jurisdictions may be different and hard to compare. Several factors may simultaneously affect waiting times and private health sector activities, driving the correlation between waiting times and PHI, but a causal link is difficult to establish.

In this paper, we examine whether changes in the PHI take-up affect waiting times in public hospitals in the state of Victoria. Victoria is the second most populous state in Australia, accounting for about 26% of the Australian population. In Australia, hospitals are managed by individual states; and therefore a uniform national hospital data collection system does not exist. We use person-level linked hospital administrative data from two key data sources: the Victorian Admitted Episodes Dataset (VAED) and the Victorian Elective Surgery Information System (ESIS), 2014/15–2017/18. These data cover all Victorian residents who had any inpatient admissions in any hospitals in Victoria (both public and private hospitals) and patient-level collection of elective surgery waiting list data from Victorian public hospitals.

Our analysis was carried out in two stages. In the first stage, using the individual patient-level data, we first aggregate waiting times to area level by quarter after adjusting for patient characteristics that may affect waiting times. In the second stage, we regress the quarterly average adjusted waiting times on PHI coverage in the region. Because PHI coverage is endogenous, we employ an instrumental variable approach to examine the causal relationship between PHI coverage among admitted patients in a region and the average waiting times experienced by public patients in the region.

Our results indicate that a one-percentage-point increase in the proportion of patients with PHI in a region on average reduces waiting times by 0.50 per cent, or approximately 0.34 days, for public patients in the region. We further find that the effects vary by surgical specialties and age groups.

To the best of our knowledge, our study is the first to investigate the causal impact of regional take-up of PHI on waiting times in public hospitals using comprehensive

Australian administrative data linked at the patient level.

The remainder of this paper is organized as follows. We describe the institutional context and related literature in Section 2, and discuss the data and econometric methods in Section 3. Section 4 presents the main results. Section 5 discusses the policy implications of our findings and Section 6 concludes.

2 Background and related literature

Australia has a universal public health insurance—Medicare, which covers free hospital treatment in public hospitals, subsidises medications, primary care and specialist treatment. All Australians (and some overseas visitors) have access to a wide range of health and hospital services at low or no cost under Medicare (Department of Health, 2021).

Like many countries with universal health insurance, non-urgent hospital treatment has a waiting list in public hospitals. As managers of the hospital system, the states manage waiting times in public hospitals directly. At the federal level, Australia has largely emphasised the role of private healthcare as the main mechanism for shifting demand away from the overburdened public hospital system. A private hospital system runs parallel to public care and provides patients with more flexible treatment options. About 40% of all inpatient admissions are in private hospitals (Australian Institute of Health and Welfare, 2022). About half of the funding to private hospitals comes from private health insurance, one third from governments and the rest from individuals as copayments.

As of December 2022, 45% of Australians are covered by PHI, higher than other countries with universal health care coverage (Australian Prudential Regulation Authority, 2023). This relatively high PHI rate is achieved by considerable government interventions: an income-based tax penalty, an age-based penalty, and means-tested rebates.

PHI typically consists of two parts: private hospital cover, and auxiliary or extra care

cover that includes dental, optical care, physiotherapy, etc. Individuals and households can buy joint covers including both parts, or only one of them. The government interventions only apply to hospital cover, not the cover for extra care (Hurley et al., 2002).

The government justified these interventions by alluding to the possibility that more people enroll in PHI may lead to greater use of the private system, which will free up resources in the public system and thereby reduce waiting times for treatment in public hospitals. However, it is unclear whether this approach could effectively reduce waiting times at the population level. Others argue that government subsidies on PHI could increase, instead of reducing, pressure on the public health system (Eckermann et al., 2016).

In addition to shorter waiting times, private patients have more flexibility in choosing care in private hospitals or as a private patient in public hospitals, the choice of attending doctors, and access to better amenities and private rooms (Zhang and Prakash, 2021). However, in addition to paying insurance premiums, private patients often incur out-of-pocket expenses due to insurance deductibles and/or gap payments between what insurers cover and what doctors charge.

The relationship between PHI and waiting times can go both ways. A few studies examined whether waiting times affect individual decisions to purchase PHI. Besley et al. (1999) found waiting for medical treatment in British public hospitals positively influenced the decision to buy PHI. Similar results were observed in studies using Spanish data (Jofre-Bonet, 2000), and Irish data (Harmon and Nolan, 2001). However, Johar et al. (2011) found that waiting times on average had no significant impact on insurance. In addition, it is not the expected waiting time (i.e., the mean) but the probability of experiencing a long wait (i.e., the right-hand tail of the distribution) that increased the likelihood to buy PHI. In addition, Johar et al. (2013) re-examined the sensitivity to the use of waiting lists as a proxy for waiting times and found that waiting lists do

not predict demand for PHI, and concluded that the impact of waiting times on PHI demand had been overstated.

On the other hand, the evidence of PHI on the length of waiting times in the public sector is mixed. In the absence of price, waiting times can serve as a nonprice rationing that affects both demand for and supply of healthcare use (Lindsay and Feigenbaum, 1984; Martin and Smith, 1999; Riganti et al., 2017). Several studies conclude that the elasticity of demand with respect to waiting time is small, but the supply side is more elastic, suggesting increasing resources for the public system is more effective (Martin et al., 2007; Siciliani and Iversen, 2012).

In theory, it is possible that government subsidies on PHI could reduce waiting time in the public system, because individuals with high waiting costs would choose private treatment (Hoel and Sæther, 2003). Empirically, little evidence establishes the causal inference, especially in the Australian context.

Several studies compared waiting times between patients with and without PHI and found that PHI patients have shorter waiting times for acute hospital care, GP and specialist care (Kuchinke et al., 2009; Whyte et al., 2020; Roll et al., 2012). However, these studies simply compared waiting times among individual patients with and without PHI, but did not study whether a higher proportion of people having PHI leads to shorter waiting times in public hospitals at the population level.

Earlier studies observed a reduction in Australian waiting times over the period 1999-2001 for selected procedures. However, this period coincided with an increase in the proportion of the population covered by PHI due to three main government interventions introduced around this time to encourage the uptake of PHI (Hanning, 2002; Siciliani and Hurst, 2003). Moreover, another study used 2001-2002 hospital data found the opposite—the median waiting time was positively related to the proportion of private patients (J Duckett, 2005). Several other studies noted conflicting results on both waiting lists and times (Hurley et al., 2002; Hopkins and Frech, 2001; Colombo and Tapay, 2003).

3 Methods and Data

3.1 Empirical strategies

We study how the average waiting time in a small geographical area is causally affected by the variation in PHI coverage in the area. For this analysis, we choose Statistical Area Level 2 (SA2) as the area-level unit. SA2 are medium-sized general purpose areas delineated to represent communities that interact together socially and economically (Australian Bureau of Statistics, 2021). Generally, the population size of a SA2 ranges from 3,000 to 25,000 people, with an average of about 10,000 people. There are 433 SA2s in Victoria.

Our analysis proceeds in two stages. In the first stage, we aggregate individual waiting times to SA2 levels for each quarter during our study period. Instead of averaging the raw waiting times of patients in each SA2, we calculate a risk-adjusted waiting time for each patient by taking advantage of our patient-level data. We first estimate the predicted waiting time after adjusting for patient risk factors that affect her waiting time, including age, gender, urgency of conditions, and place of residence by SA2. These factors are measured at the start of the waiting spell. We then calculate the adjusted waiting time and then aggregate up to each SA2 level and by quarter.

In the second stage, we estimate the effect of PHI coverage on adjusted waiting times that are aggregated at the SA2 level and by quarter. A key concern here is that PHI may be endogenous due to reversal causality. To mitigate endogeneity, we use an instrumental variables approach. The instrument is the average house price at the SA2 level and by quarter. Below we discuss our approach in greater detail.

Stage 1

In Stage 1, the waiting time (W_{irt}) of patient i in a SA2 region r at time t are risk adjusted using a log-linear regression model.

$$\log W_{irt} = X_i'\theta + \beta_r + \tau_t + \varepsilon_{irt}, \tag{1}$$

where X_i is a vector of patient characteristics (e.g., gender, age, urgency, etc.), β_r and τ_t denote area and time fixed effects, and ε_{irt} is the error term. Note that t indicates the start time in the waiting list registration (registration quarter and year in the data).

The adjusted waiting time (in logarithm), denoted by $\log W^a_{irt}$, can be computed as:

$$\log W^a_{irt} = \log W_{irt} - (X_i'\hat{\theta} + \hat{\tau}_t). \tag{2}$$

Note that the area fixed effects term, $\hat{\beta}_r$, is not included in calculating the adjusted waiting time, because area effects are not part of individual factors to be adjusted. We include it in the first-stage estimation to avoid omitted variable bias in estimating θ.

Next, we aggregate individual risk-adjusted waiting times to the SA2 level as follows.

$$\log \tilde{W}_{rt} = \frac{1}{n_{rt}} \sum_{i \in I_{rt}} \log W^a_{irt}, \tag{3}$$

where I_{rt} denotes the set of patients on the waiting list who reside in area r and begin waiting at time t, and $n_{rt} = \#I_{rt}$ is the total number of patients in the set. In effect, $\tilde{W}_{rt}$ is the geometric mean waiting time of area r at time t. The log-linear form provides a convenient interpretation of the estimated effect, as will be shown below.

Stage 2

In Stage 2, we regress the average adjusted waiting time, $\tilde{W}_{rt}$ in area r at time t to the PHI coverage, denoted P_{rt}, with the aim of identifying the causal effect of PHI on waiting times at the area level. We specify a linear model of the form:

$$\log \tilde{W}_{rt} = \alpha\, P_{rt} + Z_{rt}'\gamma + d_t'\delta + d_r'\mu + \zeta_{rt}, \tag{4}$$

where Z_{rt} denotes the vector of area characteristics, d_t and d_r denote dummy variables that respectively indicate time and area fixed effects, with ζ_{rt} denoting the error term. Because adjusted waiting time and PHI coverage are now at SA2 level, to control for the area fixed effects in (4), we use a larger area unit than SA2, Statistical Area 3 (SA3), to allow for more variation within each region.

The key variable of interest is PHI coverage at the area-quarter level, P_{rt}. This variable, however, is likely endogenous due to reverse causality—the average waiting time in an area may affect the PHI take-up rate in the area, because avoiding long waiting times for elective surgery in public hospitals is a common reason to purchase PHI.

To address the endogeneity issue, we employ an instrumental variable approach by using area-level average house prices as the instrument. We argue that local house prices are correlated with average income and wealth which is a key factor in increasing PHI purchase, due to the tax penalty designed to induce high income individuals to buy PHI. However, average house prices do not directly affect waiting times in public hospitals. We estimate (4) by two-stage least squares (2SLS).

Finally, from the linear relationship between adjusted and unadjusted waiting times and the exogeneity of X_i in (2), we note that

$$\alpha = \frac{\partial \log \tilde{W}_{rt}}{\partial P_{rt}} = \frac{1}{n_{rt}} \sum_{i \in I_{rt}} \frac{\partial \log W^a_{irt}}{\partial P_{rt}} = \frac{1}{n_{rt}} \sum_{i \in I_{rt}} \frac{\partial \log W_{irt}}{\partial P_{rt}}, \tag{5}$$

which shows that the marginal effect of PHI coverage, P_{rt}, on the adjusted waiting time is equivalent to the average effect of P_{rt} on the unadjusted waiting time.

Since an infinitesimal change in the logarithm of waiting times can be interpreted as the percentage change in waiting times, i.e.

$$\frac{\partial \log \tilde{W}_{rt}}{\partial P_{rt}} = \frac{\partial \tilde{W}_{rt} / \tilde{W}_{rt}}{\partial P_{rt}}.$$

Therefore, α in (5), being the partial elasticity of adjusted waiting times with respect to P_{rt}, can also be interpreted as the average percentage change in waiting times in an

area with respect to a one-unit change in the area's proportion of PHI coverage. This will become useful when we interpret our results in the Results section.

3.2 Data

We use two administrative data sources provided by the Victorian Department of Health. The data span the period 1 July 2014 to 30 June 2018. Hospital admission data were obtained from the Victorian Admitted Episodes Dataset (VAED), and data on waiting times were obtained from the Elective Surgery Information System (ESIS). The two data sets were linked using encrypted individual patient IDs.

VAED covers all patients in Victoria who had any inpatient admissions in all hospitals, both public and private. It is an admission episode-level data which include information on patient demographics such as age and gender, clinical details such as relevant diagnoses and comorbidity, administrative details such as insurance status, the date of admission and discharge, and whether the patient was admitted as a private or public patient.

ESIS is a patient-level collection of elective surgery waiting list data from all major Victorian public hospitals. Patients who wait to receive elective surgeries as a public patient in a public hospital are registered in the waiting list. The data include information on start date on the waiting list, exit date, intended procedure, urgency category, etc. In total, we observe 819,230 ESIS records in our data. The dataset contains waiting episodes for elective surgeries at nearly 100 public hospitals in Victoria. Not all public hospitals manage their waiting list under ESIS, although public hospitals included in ESIS account for more than 95% of all elective procedures in public hospitals in the state.

3.3 Waiting times

As per the ESIS guidelines (Victorian Department of Health, 2020), the waiting time (in days) of a patient is calculated as the difference between the date when the patient was admitted to a public hospital for the registered procedure (the admission date) and the date when the patient first entered the waiting list of the reporting hospital (the registration date). In the event that a patient is not eventually admitted into a hospital for treatment of the registered procedure and thus has no admission date, we use the 'removal date' in place of the admission date in calculating the patient's waiting time. The removal date is the date on which the patient's waiting episode is completed by events other than the planned admission. The 'Reason for Removal' code set includes fields such as "patient died, surgery declined or not required, transferred to a non-ESIS-registered hospital, etc."

3.4 PHI coverage

We define the PHI coverage of a SA2 area as the percentage of admitted patients with PHI out of all patients admitted in the SA2 area during a given time period. To construct this variable, we used the administrative data for all hospital admissions of patients residing in each SA2 area and quarter-year, together with the self-reported hospital insurance status of each patient. We think this measure provides a more accurate reflection of the potential demand for hospital care than using the proportion of residents who have PHI in each SA2 area. The latter may not be very informative because not all individuals with PHI are likely to need hospital care. Many high income individuals, for example, purchase PHI to avoid paying the tax penalty.

3.5 Exclusion criteria

Our ESIS waiting time data cover data from all patients whose ESIS administrative registration dates occurred during the four financial years, 2014/15–2017/18. In our analyses of waiting times, we apply the following exclusion criteria. First, all entries into the waiting list in the last financial year, 2017/18, i.e., registration dates between 1 July 2017 and 30 June 2018, were excluded. Because our last year inpatient admission data is 2017/18, by removing 2017/18 ESIS data, we ensure that there is at least one year to observe the exit from waiting after patients were registered on the waiting list. Including entries from 2017/18 would have severely biased the sample waiting times downward, because only those with short waiting time would have been observed in linked inpatient data and therefore included in our analyses. If the follow-up period in the inpatient data is not long enough, the waiting periods could be understated since only patients with short waiting times would be captured in the data. This criterion removed 181,356 observations (22%).

Second, we excluded patients residing outside Victoria or whose usual residential locations could not be identified (11,207 observations or 1.4%). Third, we excluded 20,427 observations (2.5%) with longer than one-year waiting times. This is because compared to those who joined the waiting list later, say, approaching the end of 2016/17, patients who were registered in earlier years, such as in 2014/15, were more likely to be observed having waited for more than 365 days. This exclusion is necessary to ensure that our estimation sample includes patients from each year and who are comparable in terms of their waiting times. As discussed in the robustness analyses below, we relax this exclusion criterion and found similar results.

After applying all exclusion criteria, we end up with a sample of 606,177 observations covering the period 2014/15 to 2016/17.

3.6 Data limitations

Our analysis uses a unique dataset that links hospital admission data with waiting list data [1]. Although comprehensive, the data nonetheless have some limitations. The waiting list data contain little information about patients; most patient characteristics were obtained from the inpatient episode data. There is, for example, no information on patients' location of residence in the waiting list data. This means our sample only captured patients who exited the waiting list *and* gained admission into a hospital. Patients who remained on the waiting list, and those who exited for reasons other than getting admitted into a hospital were not captured in our data. Second, we have to exclude one year waiting list data so we effectively only have data for three years and from one state. It is difficult to generalize our results to other states and other time periods especially during recent years with COVID-19 having severely disrupted surgery schedules in public hospitals.

4 Results

4.1 Summary statistics

We first present descriptive statistics about waiting times in our data after applying exclusion criteria mentioned above. Figure 1 shows that the distribution of waiting times is right-skewed.

Table 1 presents the mean, median and 90th percentile of waiting times for the full sample ($N = 606,177$), as well as six sub-groups, including patients with cancer diagnoses, and patients with one of three common Principal Prescribed Procedures (PPP) that are often performed in private hospitals, and patients divided into two age groups (< 55 and ≥ 55 years).

[1] The Office of Research Ethics and Integrity at the authors' institution has approved this study.

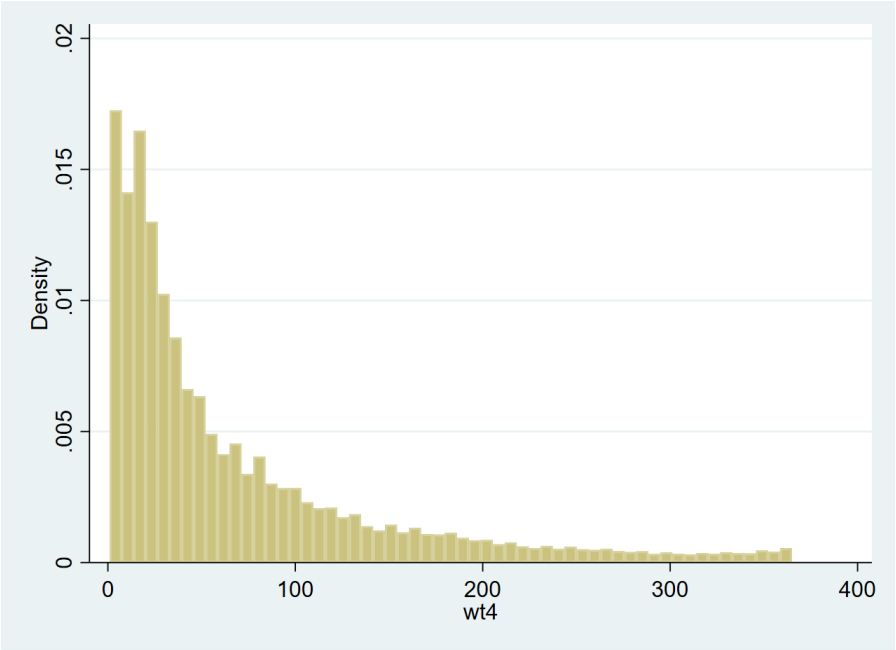

Figure 1: Distribution of waiting times

For the full sample, the mean waiting time was about 69 days, with the median and 90th percentile at around 38 and 179 days. Among the patient subgroups, patients with cancer diagnoses appeared to have the shortest waiting time on average, at around 66 days, whereas patients requiring hip and knee replacements unsurprisingly experienced the longest wait, for more than 139 and 160 days, respectively. Lastly, we note that the length of waiting between patients in the younger (< 55) and older (≥ 55) age groups did not appear to differ appreciably on average.

Table 1: Summary Statistics of Waiting Time

	Mean	Std dev	Median	90th %tile	N
Full sample	68.58	76.58	38	179	606,177
Cancer patients	66.24	68.86	40	161	28,898
Hip replacement	139.60	88.84	121	276	7,230
Repair of cataract	71.68	71.89	48	173	51,467
Knee replacement	160.89	93.43	146	305	7,892
Age < 55	67.87	75.41	39	176	293,463
Age ≥ 55	69.25	77.65	37	181	312,714

Table 2 presents summary statistics about patients in our sample. These patient char-

acteristics are used as factors in the first stage risk-adjustment of waiting times. About 51% of patients in our sample were aged 55 years or older, with more than a third older than 65 years. About a third of patients were classified to have high urgency conditions, whereas about 22% were regarded as low urgency. General surgery was the specialty procedure with the highest proportion (24%) of patients in waiting, followed by urology (15%) and ophthalmology (11%) procedures. These characteristics of patients were important factors influencing individual waiting times. The estimated coefficients of these factors from the estimation of (1) are shown in the Appendix.

Table 2: Descriptive Statistics, patient characteristics

Variable	Mean	Std dev
Age		
15<Age	0.082	0.275
15≥Age<25	0.057	0.232
25≥Age<35	0.090	0.287
35≥Age<45	0.112	0.316
45≥Age<55	0.142	0.349
55≥Age<65	0.159	0.366
65≥Age	0.357	0.479
Male	0.489	0.500
Indigenous	0.010	0.099
Episode Urgency		
High	0.329	0.470
Medium	0.450	0.498
Low	0.221	0.415
Surgical Specialty		
Cardio-thoracic surgery	0.023	0.150
Ear nose and throat surgery	0.076	0.265
General surgery	0.243	0.429
Gynaecology surgery	0.098	0.297
Neurosurgery	0.016	0.125
Ophthalmology surgery	0.114	0.318
Orthopaedic surgery	0.100	0.300
Plastic surgery	0.091	0.287
Urology surgery	0.147	0.355
Vascular surgery	0.019	0.137
Other	0.072	0.259

After estimating the stage 1 adjustment equation, we aggregate waiting times by region-

quarter to obtain the average waiting time for each SA2 area and by quarter. This yields 4,993 observations in the SA2-quarter aggregate sample.

Table 3 presents the descriptive statistics of area-level characteristics we used as controls in estimating (4). All variables were aggregated up to SA2-quarter level, with the exception of the number of aged care places and the volume of GP services. In particular, the former was aggregated up to a larger area called the Aged Care Planning Region, which typically includes several neighbouring SA2 areas, and the latter was also only observed at the SA3 level.

The PHI coverage of the SA2 areas in our sample ranged from 0% to 89%, with a mean of about 44%. The average area had about 0.59 ED presentations per 100 residents and 3 hospital admissions per 100 residents each quarter. There were about 604 general practitioner (GP) visits per 100 residents across SA3 regions. The average number of aged care places per 100 residents across ACPR regions was about 0.9 places. On average, there were slightly more female patients than male patients, with approximately one-third of all patients in the age range 40–64 years. The mean of average area house price was A$540,000.

Table 3: Descriptive Statistics, area characteristics

Variable	Mean	Std dev	Min	Max
PHI coverage (%)	43.948	16.877	0.000	88.889
Male hospital patients (%)	47.799	4.926	23.077	100.000
Hospital patients aged 0–19 (%)	9.629	3.147	0.000	42.857
Hospital patients aged 20–39 (%)	16.958	6.042	0.000	47.191
Hospital patients aged 40–64 (%)	32.442	5.608	0.000	100.000
GP Services (per 100 residents)	603.860	80.176	402.923	803.880
Hospital ED presentations (per 100 resi)	0.587	0.289	0.000	3.214
Hospital admissions (per 100 resi)	2.959	1.126	0.011	13.131
House price (AUD)	540,358	316,209	136,403	3,550,963
Area population (log)	10.741	0.664	4.595	11.955
Aged care places in ACPR (per 100 resi)	0.916	0.207	0.542	1.233

Notes: Aged Care Planning Regions (ACPR) are used to define aged care regions; each ACPR consists of several neighbouring SA2 areas. The volume of GP Services is observed at the SA3 level.

4.2 Estimation results

We report our main estimation results in Table 4, which shows the results of three 2SLS specifications and the OLS estimation. All regressions include year, quarter, and SA3 region dummies. Specification I is the simplest, which uses no area level characteristics as controls. Specification II adds characteristics of patients in each SA2 area, while Specification III includes additional area-level characteristics. The reported coefficients can be interpreted as the average marginal effects of the respective explanatory variables on average adjusted waiting times (in log) from the second stage of our 2SLS estimation of (4). Estimates from the first stage estimation of the three 2SLS specifications can be found in the Appendix (Table A.2).

Table 4: Coefficient Estimates, 2SLS and OLS estimation

	2SLS						OLS	
	Specification I		Specification II		Specification III			
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
PHI coverage (pp)	-0.0047	<0.001	-0.0047	<0.001	-0.0050	<0.001	-0.0022	<0.001
	(0.0005)		(0.0005)		(0.0006)		(0.0003)	
Male hospital patients (pp)	–		-0.0010	0.097	-0.0005	0.405	0.0004	0.520
			(0.0006)		(0.0006)		(0.0006)	
Hospital patients aged 0–19 (pp)	–		-0.0019	0.126	-0.0016	0.190	-0.0021	0.088
			(0.0012)		(0.0012)		(0.0012)	
Hospital patients aged 20–39 (pp)	–		0.0001	0.869	0.0004	0.585	0.0016	0.039
			(0.0008)		(0.0008)		(0.0008)	
Hospital patients aged 40–64 (pp)	–		-0.0004	0.463	-0.0001	0.836	-0.0007	0.180
			(0.0005)		(0.0005)		(0.0005)	
Aged Care places (per 100 resi)	–		–		-0.0479	0.419	-0.0048	0.934
					(0.0593)		(0.0588)	
GP Services (per 100 resi)	–		–		0.0014	<0.001	0.0014	<0.001
					(0.0003)		(0.0003)	
ED presentations (per 100 resi)	–				-0.1222	<0.001	-0.0231	0.367
					(0.0314)		(0.0256)	
Hospital admissions (per 100 resi)	–		–		0.0216	0.002	0.0005	0.937
					(0.0071)		(0.0061)	
Area population (log)	–		–		0.0215	<0.001	0.0294	<0.001
					(0.0051)		(0.0050)	
Constant	0.2198	<0.001	0.2953	<0.001	-0.7369	<0.001	-1.0165	<0.001
	(0.0327)		(0.0550)		(0.2091)		(0.2048)	
Cragg-Donald F test	2,337.5	<0.001	2,149.7	<0.001	1,634.0	<0.001	–	
N	4,968		4,968		4,968		4,970	

Notes: Figures in parentheses are standard errors. Also included in all regressions are 3 year dummies, 3 quarter dummies, and 64 SA3 region dummies.

The key variable of interest is PHI coverage, which is measured using the proportion of admitted patients with PHI out of all admitted patients in each SA2 area. The coefficient

estimate suggests that areas with higher PHI coverage experienced lower waiting times on average. According to (5), the estimated effect suggests that a one percentage point increase in PHI coverage in an area reduces waiting times in public hospitals in the area by about 0.5%, or approximately 0.3 days of waiting if we use the sample mean waiting time of 69 days as a guide. A comparison with the OLS estimate of 0.22% suggests that the presence of endogeneity bias over-estimates the effect of PHI coverage on waiting time, due perhaps to the reverse causality of high waiting times inducing individuals to purchase PHI to avoid waiting in public hospitals.

It is noteworthy that the first stage F-statistics of the excluded instrument in all three specifications are comfortably larger than Stock and Yogo (2005) critical value of 16.38 for a type-1 error of 5% and a maximum 10% relative bias with respect to OLS, indicating strong identification.

Other coefficient estimates in Table 4 are difficult to interpret, since they capture area-level aggregate effects, which are likely affected by a confluence of factors. For example, areas with a larger population, more hospital admissions, and higher GP service volume seem to imply longer average waiting times in the area. All these factors could imply higher demand for healthcare services, which may suggest greater demand for hospital care and longer waiting times. Other possibilities such as the complexity of patient health conditions may also be reflected in the volume of hospital admissions and GP service volume. Another area characteristic that plays a role was the volume of ED presentations in the area, which was found to reduce waiting times. This may reflect the urgency of health needs due to emergency health events, which would imply shorter waiting times.

4.3 Heterogeneity and robustness analyses

Heterogeneity analyses

We conduct heterogeneity analyses on several sub-samples categorized by age and procedure. Because waiting times vary depending on the type of procedures required, it is reasonable to hypothesize that the effect of area PHI coverage on waiting times could also vary by procedure. Table 5 presents the coefficient estimates of PHI coverage on adjusted waiting times, along with the equivalent number of days of waiting calculated using the respective sample mean as a reference point. All coefficients are estimated under specification III in Table 4 using 2SLS with average housing prices (log) in the area serving as the IV. The estimate for the full sample is also provided for comparison. Sub-samples analyzed include patients in two age categories (< 55 years and ≥ 55 years), patients with PPP codes related to cancer, cataract surgery, hip replacement and knee replacement, and patients in ten mutually exclusive surgical speciality groups including cardio-thoracic surgery, ear nose and throat (ENT) surgery, general surgery, gynaecology, neurosurgery, ophthalmology, orthopaedic surgery, plastic surgery, urology and vascular surgery.

We find that the effects of PHI do vary by age and across some surgical procedures. For patients older than age 55, an increase in the area PHI coverage appeared to have a somewhat larger effect than on patients younger than 55. The former showed a reduction of 0.38 days in waiting in comparison to the latter's 0.31 days reduction. The difference quite possibly reflects the types of procedures older and younger age groups tend to require. For cancer patients and those waiting for plastic surgery and ophthalmology procedures, an increase in PHI coverage was found to reduce waiting times by a smaller extent than the average patient. On the other hand, PHI coverage appeared to have larger effects on the waiting times of patients waiting for general surgery, ear, nose & throat (ENT) surgery, orthopaedic surgery, and neurosurgery. It is worth noting, however, that all these specialty fields, with the exception of general surgery, had longer

average waiting periods than the full sample.

Robustness

Our estimation sample does not include patients who waited on the waiting list for more than one year. In order to investigate whether our findings are robust to this exclusion, we re-estimated our preferred 2SLS Specification III on two alternative samples: 1) excluding patients who waited longer than 730 days, and 2) including all patients without any exclusion based on waiting length. The resulting estimates, shown in the Appendix (Table A.3), are similar to our main results presented earlier in Table 4, indicating the robustness of our findings. This also applies to the sub-samples.

5 Discussions

The healthcare systems in many countries face the ongoing challenges of balancing the competing demands of providing equitable access to care for all citizens while also striving to achieve efficiency and cost-effectiveness. One area where these goals intersect is the management of waiting times for elective procedures that are publicly funded (Hurst and Siciliani, 2003). Waiting time is an important indicator of the performance of a healthcare system, because long waiting periods significantly affect patient health outcomes and satisfaction, and may increase downstream medical costs as well (Ballini et al., 2015). In Australia's mixed public-private health system, waiting times in public hospitals can be affected by changes in the private healthcare sector, through changes on PHI coverage and subsequent use of private hospitals.

Our study investigates the impact of small area-level changes in PHI coverage on waiting times in public hospitals. We are the first to use comprehensive data that link hospital administrative data with elective surgery waiting list data to study this important question. We show that the extent of PHI coverage in a geographic area can have a

Table 5: Sub-sample analysis, Specification III, 2SLS estimation of adj. waiting time (log) on area PHI coverage

Dependent variable: log(Adjusted waiting time)				
	PHI coverage Coeff.	p-value	Equiv. no. days	Mean waiting times (days)
Full sample	-0.0050	<0.001	-0.342	68.6
	(0.0006)			
Sub-sample:				
Age < 55 years	-0.0045	<0.001	-0.305	67.9
	(0.0008)			
Age ≥ 55 years	-0.0055	<0.001	-0.380	69.3
	(0.0008)			
Cancer patients	-0.0041	0.014	-0.271	66.3
	(0.0017)			
Hip replacement	-0.0029	0.251	-0.404	139.6
	(0.0026)			
Cataract surgery	-0.0028	0.207	-0.200	71.7
	(0.0022)			
Knee replacement	-0.0031	0.212	-0.498	160.8
	(0.0025)			
Urology procedures	-0.0005	0.646	-0.034	68.2
	(0.0011)			
Cardio-thoracic surgery	-0.0001	0.985	0.004	36.2
	(0.0030)			
Ophthalmology	-0.0046	0.014	-0.325	70.8
	(0.0019)			
General surgery	-0.0071	<0.001	-0.452	63.9
	(0.0011)			
Ear, nose & throat surgery	-0.0096	<0.001	-0.870	91.1
	(0.0018)			
Orthopaedic surgery	-0.0049	0.001	-0.476	97.4
	(0.0015)			
Gynaecology surgery	-0.0024	0.110	-0.130	54.4
	(0.0015)			
Neurosurgery	-0.0089	0.003	-0.671	75.7
	(0.0030)			
Plastic surgery	-0.0035	0.025	-0.186	53.2
	(0.0016)			
Vascular surgery	0.0046	0.111	0.367	79.5
	(0.0029)			

Notes: Figures in parentheses are standard errors.The Cragg-Donald Wald F Statistic for all 2SLS sub-sample estimations are well above the Stock-Yogo weak identification critical value 16.38 at 10% maximal IV size, indicating strong identification.

statistically significant impact on waiting times in public hospitals. Areas with higher PHI take-up tend to have shorter waiting times in public hospitals, after adjustment for other area-level characteristics that may affect waiting times. However, the estimated

effect is small in practical terms—an increase of PHI coverage by a percentage point reduces waiting time by about 0.5% or about 0.3 days. Patients in our sample waited on average about 69 days, with a median waiting time of 38 days.

Our findings have important policy implications. First, although policies aiming at increasing the uptake of PHI may have a statistically significant effect on reducing waiting times for elective procedures in public hospitals, in practice the effect is small. Second, the Australian government has introduced several policy interventions to encourage individuals to enroll in PHI, including premium subsidies and age and tax penalties (Palangkaraya and Yong, 2005). Some of these interventions have been costly in fiscal terms. On balance, the small reduction in waiting times in public hospitals cannot justify the large fiscal costs. The money spent on rebates and subsidies could be more cost-effectively invested in other programs, including investing directly in public hospitals and chronic disease prevention in primary care (Martin and Smith, 1999; McPake and Mahal, 2017). Third, individuals who purchase PHI and bypass waiting times are more likely to be high income earners; this creates an inequality in access to healthcare.

Our findings suggest that policy interventions targeting at increasing PHI take-up will not have meaningful effect on reducing elective surgery waiting times. Instead, the government should consider other approaches, for example, investing in innovative care delivery and funding models, strengthening community health services and community-based care, chronic disease prevention in primary care, or even purchasing services directly from private hospitals (McPake and Mahal, 2017; Eckermann et al., 2016).

Lastly, policymakers may want to consider the broader systemic issues that will require structural reforms to the healthcare system, such as changing the funding and governance arrangements to address the underlying fundamental challenges facing the health system. Regional issues, including health workforce shortages, fragmentation of care and regional imbalances in matching capacity to healthcare needs, remain pressing issues requiring policy interventions (Siciliani et al., 2015; OECD, 2013; Siciliani and Hurst, 2005).

6 Conclusions

We investigate the impact of increasing private health insurance coverage on waiting times in public hospitals in Australia. We find that the effect, while statistically significant, is small in practical terms. The small effect suggests that raising PHI coverage, with the aim to increase private care and therefore take the pressure off the public system, is not an effective and practical strategy in reducing waiting times for elective surgery in public hospitals. Alternative policies aiming at improving the efficiency of public hospitals and advancing equitable access to care should be a priority for policy-makers.

References

Australian Bureau of Statistics (2021). Australian Statistical Geography Standard (ASGS) Edition 3. Available at https://www.abs.gov.au/statistics/standards/australian-statistical-geography-standard-asgs-edition-3/jul2021-jun2026. Accessed February 16, 2023.

Australian Institute of Health and Welfare (2022). Australia's hospitals at a glance. Available at https://www.aihw.gov.au/reports/hospitals/australias-hospitals-at-a-glance/contents/hospital-activity.

Australian Prudential Regulation Authority (2023). Quarterly private health insurance statistics. Available at https://www.apra.gov.au/quarterly-private-health-insurance-statistics. Accessed March 17, 2023.

Ballini, L., A. Negro, S. Maltoni, L. Vignatelli, G. Flodgren, I. Simera, J. Holmes, and R. Grilli (2015). Interventions to reduce waiting times for elective procedures. In *Cochrane Database of Systematic Reviews*. Cachrane Library. doi.org/10.1002/14651858.CD005610.pub2.

Besley, T., J. Hall, and I. Preston (1999). The demand for private health insurance: do waiting lists matter? *Journal of public economics 72*(2), 155–181.

Colombo, F. and N. Tapay (2003). Private Health Insurance in Australia: A Case Study. *OECD Health Working Papers*, No. 8, OECD Publishing, Paris.

Department of Health (2021). Medicare. Available at https://www.health.gov.au/health-topics/medicare. Accessed June 10, 2021.

Duckett, S. and K. Nemet (2019). *The history and purpose of private health insurance*. Grattan Institute.

Eckermann, S., L. Sheridan, and R. Ivers (2016). Which direction should australian health system reform be heading? *Australian and New Zealand journal of public health 40*(1), 7–9.

Hanning, B. (2002). Has the increase in private health insurance uptake affected the Victorian public hospital surgical waiting list? *Australian Health Review 25*(6), 64.

Harmon, C. and B. Nolan (2001). Health insurance and health services utilization in ireland. *Health economics 10*(2), 135–145.

Hoel, M. and E. M. Sæther (2003). Public health care with waiting time: the role of supplementary private health care. *Journal of health economics 22*(4), 599–616.

Hopkins, S. and H. Frech (2001, dec). The Rise of Private Health Insurance in Australia: Early Effects on Insurance and Hospital Markets. *The Economic and Labour Relations Review 12*(2), 225–238.

Hurley, J., R. Vaithianathan, T. F. Crossley, and D. A. Cobb-Clark (2002). Parallel private health insurance in australia: A cautionary tale and lessons for canada. *SSRN Electronic Journal*.

Hurst, J. and L. Siciliani (2003). Tackling excessive waiting times for elective surgery: A comparison of policies in twelve oecd countries. OECD Health Working Papers 6, OECD Publishing. doi.org/10.1787/108471127058.

J Duckett, S. (2005). Private care and public waiting. *Australian Health Review 29*(1), 87.

Jofre-Bonet, M. (2000). Public health care and private insurance demand: the waiting time as a link. *Health Care Management Science 3*(1), 51–71.

Johar, M., G. Jones, M. Keane, E. Savage, and O. Stavrunova (2011, sep). Waiting times for elective surgery and the decision to buy private health insurance. *Health Economics 20*(S1), 68–86.

Johar, M., M. Keane, and O. Stavrunova (2013). "The Demand for Private Health Insurance: Do Waiting Lists Matter?" – Revisited. Available at `https://www.nuffield.ox.ac.uk/economics/papers/2013/Besley_2013.pdf`. Accessed December 20, 2021.

Kuchinke, B. A., D. Sauerland, and A. Wübker (2009, dec). The influence of insurance status on waiting times in German acute care hospitals: an empirical analysis of new data. *International Journal for Equity in Health 8*(1), 44.

Lindsay, C. M. and B. Feigenbaum (1984). Rationing by waiting lists. *The American economic review 74*(3), 404–417.

Martin, S., N. Rice, R. Jacobs, and P. Smith (2007). The market for elective surgery: Joint estimation of supply and demand. *Journal of health economics 26*(2), 263–285.

Martin, S. and P. C. Smith (1999). Rationing by waiting lists: an empirical investigation. *Journal of Public Economics 71*(1), 141–164.

McPake, B. and A. Mahal (2017). Addressing the needs of an aging population in the health system: the australian case. *Health Systems & Reform 3*(3), 236–247.

OECD (2013). *Waiting Time Policies in the Health Sector: What Works?* Luigi Siciliani, Michael Borowitz and Valerie Moran (Ed.), OECD Health Policy Studies, OECD Publishing, Paris.

Palangkaraya, A. and J. Yong (2005). Effects of recent carrot-and-stick policy initiatives on private health insurance coverage in australia. *Economic Record 81*(254), 262–272.

Riganti, A., L. Siciliani, and C. V. Fiorio (2017). The effect of waiting times on demand and supply for elective surgery: Evidence from italy. *Health economics 26*, 92–105.

Roll, K., T. Stargardt, and J. Schreyögg (2012, oct). Effect of Type of Insurance and Income on Waiting Time for Outpatient Care. *The Geneva Papers on Risk and Insurance - Issues and Practice 37*(4), 609–632.

Siciliani, L. and J. Hurst (2003). Explaining Waiting Times Variations for Elective Surgery Across OECD Countries. *OECD Health Working Papers*, No. 7, OECD Publishing, Paris.

Siciliani, L. and J. Hurst (2005). Tackling excessive waiting times for elective surgery: a comparative analysis of policies in 12 oecd countries. *Health policy 72*(2), 201–215.

Siciliani, L. and T. Iversen (2012). Waiting times and waiting lists. In *The Elgar Companion to Health Economics, Second Edition*, Chapter 24. Edward Elgar Publishing.

Siciliani, L., V. Moran, M. Borowitz, et al. (2015). What works? waiting time policies in the health sector. *Eurohealth 21*(4), 14–17.

Stock, J. and M. Yogo (2005). Testing for weak instruments in linear iv regression. In D. W. Andrews (Ed.), *Identification and Inference for Econometric Models*, pp. 80–108. New York: Cambridge University Press.

Victorian Department of Health (2020). Elective Surgery Information System (ESIS) manual 2020–21. Available at `https://www.health.vic.gov.au/data-reporting/elective-surgery-information-system-esis`. Accessed February 16, 2023.

Whyte, R., S. Connolly, and M.-A. Wren (2020, nov). Insurance status and waiting times for hospital-based services in Ireland. *Health Policy 124*(11), 1174–1181.

Willcox, S., M. Seddon, S. Dunn, R. T. Edwards, J. Pearse, and J. V. Tu (2007, jul). Measuring And Reducing Waiting Times: A Cross-National Comparison Of Strategies. *Health Affairs 26*(4), 1078–1087.

Zhang, Y. and K. Prakash (2021). Why do Australians buy private hospital insurance. Available at `https://melbourneinstitute.unimelb.edu.au/__data/assets/pdf_file/0004/3800758/ri2021n06.pdf`. Accessed June 4, 2021.

Appendix (Supplementary material)

A Regression Results

Table A.1: Estimation results, waiting times risk adjustment equation

	Coeff.	s.e.	p-value
Male	-0.0407	(0.0028)	<0.001
Age (Ref: Age < 15 years)			
15≥Age<25	-0.0488	(0.0070)	<0.001
25≥Age<35	0.0125	(0.0064)	0.052
35≥Age<45	0.1307	(0.0062)	<0.001
45≥Age<55	0.2355	(0.0059)	<0.001
55≥Age<65	0.3055	(0.0058)	<0.001
65≥Age	0.3577	(0.0054)	<0.001
Indigenous status	0.0579	(0.0129)	<0.001
Episode Urgency (Ref: High)			
Medium	1.3816	(0.0030)	<0.001
Low	1.8979	(0.0039)	<0.001
Registration year (Ref: 2014)			
2015	0.0398	(0.0042)	<0.001
2016	0.0061	(0.0041)	0.141
2017	-0.0218	(0.0054)	<0.001
Registration quarter (Ref: Q1)			
2nd quarter	-0.0140	(0.0036)	<0.001
3rd quarter	0.0147	(0.0041)	<0.001
4th quarter	0.0697	(0.0041)	<0.001
Constant	2.0501	(0.0111)	<0.001

Notes: Figures in parentheses are standard errors . Also included in the estimation are 10 surgical speciality field dummies and 426 SA2 dummies.

Table A.2: 2SLS estimation results: 1st stage estimation

	Specification I		Specification II		Specification III	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
House price (log)	28.1653	<0.001	26.7883	<0.001	23.5092	<0.001
	(0.5826)		(0.5778)		(0.5816)	
Male hospital patients (pp)	–		-0.1090	<0.001	-0.1044	<0.001
			(0.0256)		(0.0248)	
Hospital patients aged 0–19 (pp)	–		0.1455	0.005	0.1358	0.006
			(0.0522)		(0.0499)	
Hospital patients aged 20–39 (pp)	–		-0.4728	<0.001	-0.3214	<0.001
			(0.0330)		(0.0325)	
Hospital patients aged 40–64 (pp)	–		0.0594	0.010	0.0710	0.001
			(0.0231)		(0.0223)	
Aged Care places (per 100 resi)	–		–		-4.2511	0.081
					(2.4350)	
GP Services (per 100 resi)	–		–		0.0615	<0.001
					(0.0128)	
ED presentations (per 100 resi)	–		–		-22.7730	<0.001
					(1.0363)	
Hospital admissions (per 100 resi)	–		–		4.6132	<0.001
					(0.2524)	
Area population (log)	–		–		0.1821	0.387
					(0.2104)	
Constant	-298.2773	<0.001	-271.3579	<0.001	-263.2332	<0.001
	(7.3564)		(7.5513)		(11.9586)	
No. observations	4,968		4,968		4,968	

Figures in parentheses are standard errors. Also included in all regressions are 3 year dummies, 3 quarter dummies and 64 SA3 dummies.

Table A.3: Estimation results, robustness analyses

	Alternative Sample I		Alternative Sample II	
	Coeff.	p-value	Coeff.	p-value
PHI coverage	-0.0052	<0.001	-0.0052	<0.001
	(0.0006)		(0.0006)	
Male hospital patients (pp)	-0.0010	0.130	-0.0010	0.133
	(0.0006)		(0.0006)	
Hospital patients aged 0–19 (pp)	-0.0016	0.210	-0.0016	0.214
	(0.0013)		(0.0013)	
Hospital patients aged 20–39 (pp)	0.0008	0.378	0.0009	0.283
	(0.0009)		(0.0009)	
Hospital patients aged 40–64 (pp)	-0.0002	0.679	-0.0001	0.823
	(0.0006)		(0.0006)	
Aged Care places (per 100 resi)	0.0092	0.882	0.00596	0.925
	(0.0620)		(0.0624)	
GP Services (per 100 resi)	0.0016	<0.001	0.0015	<0.001
	(0.0003)		(0.0003)	
ED presentations (per 100 resi)	-0.1364	<0.001	-0.1429	<0.001
	(0.0328)		(0.0330)	
Hospital admissions (per 100 resi)	0.0231	0.002	0.0245	0.001
	(0.0075)		(0.0075)	
Area population (log)	0.0268	<0.001	0.0267	<0.001
	(0.0053)		(0.0054)	
Constant	-0.9113	<0.001	-0.8907	<0.001
	(0.2189)		(0.2201)	
Cragg-Donald F test	1,634.0	<0.001	1,634.0	<0.001
No. observations	4,968		4,968	

Notes: Sample I only excluded patients who waited longer than 730 days; Sample II included all patients. Figures in parentheses are standard errors. Also included in all regressions are 3 year dummies, 3 quarter dummies and 64 SA3 dummies.


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