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Working Paper Series

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Working Paper No.10/23
August 2023

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Melbourne Institute Working Paper No. 10/23
August 2023

Conflict of interest: Authors do not have conflict of interests.

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This research was funded by an NHMRC Partnership Grant (Grant ID: 567217) and in collaboration with the Victorian Department of Health and Human Services (DHHS).

The views expressed herein are those of the authors and do not necessarily reflect the view of DHHS. We are grateful to Dr Elizabeth Paratz for her advice and insights on how a cardiology catheterisation laboratory functions. Any errors and omissions remain ours and ours only. The research has received ethics approval from the Humanities and Applied Sciences Human Ethics Sub-Committee of the University of Melbourne.

This working paper has also been submitted to SSRN and has been accepted for publication in the Journal of Economic Behavior and Organization.

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Abstract

This paper examines the role of socioeconomic status (SES) in affecting access to care and the survival of acute myocardial infarction (AMI) patients in Australia's universal health care system. We jointly model the probabilities of patients being admitted to a catheterisation-capable hospital, receiving invasive coronary angiography (ICA), and surviving 30 days post discharge as a recursive system of probit equations. We further investigate the role of capacity and whether the access gap between SES groups widens when capacity becomes limited.

Our study shows that SES plays a significant role in affecting the survival of AMI patients, both directly and indirectly through healthcare access. We find that socioeconomically disadvantaged patients are less likely to gain access to crucial services like catheterisation hospitals and ICA, which indirectly affects their survival probability in addition to the adverse direct impact of SES. While healthcare capacity showed no overall effect on access, its interplay with SES exacerbates the access disparity in situations of limited capacity. Our findings suggest that, to reduce inequality in health outcomes, public health strategy needs to focus not only on enhancing access but also addressing the direct consequences of SES.

JEL classification: I14; I18

Keywords: Socioeconomic status; Acute myocardial infarction; Coronary angiography; Health care access; Capacity.

1 Introduction

Cardiovascular disease is one of several noncommunicable diseases that account for a significant proportion of premature deaths across all countries and socioeconomic groups (Sacco et al., 2016; Stringhini et al., 2017). Although overall cardiovascular care is improving in most countries, evidence suggests that the advance favours individuals in the affluent group, which can widen the gap in health inequality over time (Bajekal et al., 2013; Schultz et al., 2018). Practitioners have highlighted the importance of public health strategies to reduce the disparities in prevention, disease risks, access to medication and specialised care, and to address the complex relationship between socioeconomic disadvantages and poor cardiovascular disease outcomes. Socioeconomic status (SES) can affect access to care, which in turn impinges on outcomes. It also has a direct bearing on poor outcomes because of lack of education and low awareness (Cutler and Lleras-Muney, 2010). An understanding of the relative importance of direct and indirect effects of SES is paramount to the formulation of an effective and targeted public health response.

We examine the role of SES in the context of Australia's universal health care system under which equity in access to care has been a stated policy priority. We ask whether SES affects acute myocardial infarction (AMI, or heart attack) patients' access to invasive coronary angiography (ICA) and subsequent survival. We measure SES in three ways: (i) remoteness of residence; (ii) Socio-Economic Indexes for Areas (SEIFA), a small-area based measure of neighborhood socioeconomic status published by the Australian Bureau of Statistics (ABS), see ABS (2013); (iii) private patient status, an indicator of whether the individual patient was admitted as a private or public patient.

We use three distinct measures of SES to capture the multifaceted nature of SES, which relates to a complex array of factors reflecting the social and economic standings of individuals. By using these three measures, we aim to present a comprehensive and nuanced picture of how different components of SES may relate to access to care and

the survival of AMI patients in Australia.

These three measures are related and complementary to one another[1]. Remoteness captures the geographic dimension of SES, which is particularly relevant Australia's vast geography and significant access disparities between rural and urban regions. Nevertheless, it does not directly measure individual or household socio-economic standings. SEIFA, on the other hand, is a well-established, comprehensive, and nationally recognized measure of area-level SES that considers a broad range of indicators (income, education, employment, etc.). However, being an area-level measure, SEIFA may not perfectly represent the SES of individual residents. By contrast, private patient status provides insight into individuals ability and choice to access private healthcare. It is known to be highly correlated with income and wealth in the context of Australia's mixed public-private insurance system because the taxation provision and premium subsidy in relation to private health insurance have provided strong financial incentives for high-income earners to purchase private health insurance (Palangkaraya and Yong, 2005).

AMI is a life-threatening emergency condition for which immediate care is required. Current best-practice guidelines suggest that the diagnosis and management of AMI should begin immediately at the point of first medical contact (Ibanez et al., 2018). ICA is a key diagnostic procedure to assess the extent of artery blockage in order to prescribe appropriate management strategies for AMI. The procedure involves the insertion of a tube (catheter) into a large arterial blood vessel and the use of a special dye and x-rays to examine blood flows through the coronary arteries. It is widely accepted that, for patients with more urgent types of AMI, ICA should be undertaken within 90 minutes and typically no more than 24 hours upon admission (Brodie et al., 2010; Sanz-Sanchez and G.G. Stefanini, 2022). For all AMI patients, timely ICA is critical for patient

[1]A correlation analysis using Goodman and Kruskal's γ between pairs of measures indicates that SEIFA is moderately correlated with remoteness of residence ($\gamma = 0.45$) and private patient status ($\gamma = 0.29$), while remoteness of residence and private patient status are weakly correlated ($\gamma = 0.01$). The analysis demonstrates that, while these measures are related, they are not perfectly collinear and thus likely capture different dimensions of SES. The moderate to weak correlations supports our decision to include all three in our analysis, as they each provide unique information about SES.

wellbeing and has a significant effect on survival (Wright et al., 2011).

ICA takes place in a catheterisation laboratory, a purpose-built facility in which a range of diagnostic and interventional cardiac procedures are performed, including ICA, percutaneous coronary intervention or stenting, pacemaker implants and replacements, etc.

We estimate a recursive system of three probit equations that model the probability of an AMI patient: (i) getting admitted to a hospital capable of performing ICA, (ii) receiving ICA, and (iii) surviving post discharge for at least 30 days. By estimating a recursive system, we are able to decompose the total effects into direct and indirect effects of SES on mortality outcomes. The indirect effects are via access to hospitals with proper facilities and receiving the appropriate treatment after admission. These are in contrast to the direct effects which affect survival due to differences in SES.

We further investigate the role of short term capacity of hospitals to deliver ICA. For patients admitted to a particular hospital, due to the urgent nature of AMI, the short-term capacity of the hospital to deliver ICA on admission is an important consideration. We investigate the interactions of SES with the short-term capacity of the admitting hospital on the day of admission. The interaction effects enable us to examine whether access to ICA differs between SES groups when capacity is low and rationing may become necessary.

We find that SES has large direct effects on access and survival of AMI patients and in some instances the inequity in access adversely affects the survival of the disadvantaged. We further find that the interactions of SES and capacity indicate that inequity in access worsens when capacity is limited and rationing may be necessary.

We contribute to the literature by proposing a recursive system of probit equations to disentangle the direct and indirect effects of SES; in addition we examine the interaction effects of SES with short-term capacity, an issue that has yet to receive attention in the literature. Our focus on direct and indirect effects of SES is similar in spirit to Hagen et

al. (2015), although our approach is different. Specifically, Hagen et al. (2015) estimate systems of independent linear equations and apply path analysis to identify the direct and indirect effects, whereas we rely on the recursive structure of our model.

Related Literature

It is well known that lower SES is associated with poorer health and higher disease risks (Braveman, et al., 2011; Matetic et al., 2020; Lago-Peñas et al., 2021). In a review of 47 studies on OECD countries, Lago-Peñas et al. (2021) conclude that low SES increases the risk of developing cardiovascular and other non-communicable diseases. Whether the poorer health is translated into greater health care use is uncertain, and much depends on the nature of care and the social support and health systems under which health care is accessed (Yong and Yang, 2021). In terms of mortality outcomes, Stringhini et al. (2017) report that, in a multicohort study of 1.7 million individuals followed up for an average of 13 years, lower SES individuals generally have higher mortality risks and this finding holds across countries and health systems. However, it is unclear whether the difference in mortality is due to lower SES individuals having poorer health or poorer access to care. On the latter, some recent evidence suggests that the increasing use of financial incentives in health care provision of care may have exacerbated the disparity in access between SES groups (Beckert and Kelly, 2021; Milcent and Zbiri, 2022).

Specific to coronary heart disease, there is a large literature on the role of SES and how it affects disease risk, access and outcomes. It is generally agreed that socioeconomically disadvantaged individuals tend to have higher coronary heart disease risks (Paige et al., 2018) and lower access to care, including access to ICA and revascularisation (Pilote et al., 2003; Hetemaa et al., 2006; Sulo et al., 2016; Schröder et al., 2016; De Luca et al. 2016; Matetic et al., 2020). Several studies also report differential access to newer treatment options in favour of high SES patients (Korda et al., 2011; Yong et al., 2014).

A natural question that arises is whether the lower access by SES disadvantaged patients

results in worse mortality outcomes. Several studies show that the differential access to care across SES groups has negligible or no effects on survival (Gnavi et al. 2014; Hagen et al., 2015; Biswas et al., 2019; Christensen et al., 2020). However, other studies have found a significant relationship between lower SES and higher mortality risks (Cafagna and Seghieri, 2017; Bergström et al., 2015; Stringhini et al., 2017; Matetic et al., 2020). Generally, in countries with strong universal health care and social protection systems, such as Sweden and Norway, SES was found to have no impact on survival. In contrast, in countries without universal health insurance such as the United States, SES tends to affect both access and survival. However, with the exception of Hagen et al. (2015), none of these studies have attempted to separate the indirect and direct effects of SES. We contribute to this literature by showing that SES plays both a direct and indirect role in affecting survival. Separating direct and indirect effects may be helpful in reconciling the mixed findings in previous studies. Our study also adds to the literature by considering how SES interacts with short-term capacity of hospitals to affect access to care.

2 Empirical Model

We distinguish between two types of AMI, ST-elevation myocardial infarctions (STEMI) and Non-ST-elevation myocardial infarctions (NSTEMI). Although under current best-practice guidelines, both types of AMI patients should receive ICA as soon as possible, they differ in urgency (Wright et al., 2011) and, as will be shown below, in patient characteristics. These differences have implications on the treatment options and survival, and more importantly, on how the availability of short-term capacity affects access and subsequent survival.

For each type of AMI, we implement a recursive system of three probit equations with dependent variables (y_{1i}, y_{2i}, y_{3i}), which respectively denote the observed binary outcome of whether patient i: (i) is admitted to a catheterisation capable hospital, (ii) receives ICA, and (iii) survives 30 days post discharge. Underlying each of the binary outcomes

is a latent index such that:[2]

$$y_{ji} = \begin{cases} 1 & \text{if } y^*_{ji} > 0; \\ 0 & \text{otherwise.} \end{cases}$$

where $j = 1, 2, 3$. For each patient i, let S_i denote a vector of SES variables, X_{ji} denote a vector of personal characteristics, and A_i is a scalar denoting the available capacity on admission. The latent indices are related to the observed covariates as follows:

$$y^*_{1i} = S_i\theta_1 + X_{1i}\beta_1 + \epsilon_{1i} \tag{1}$$

$$y^*_{2i} = y_{1i}\gamma + S_i\theta_2 + \alpha A_i + (A_i \times S_i)\lambda + X_{2i}\beta_2 + \epsilon_{2i} \tag{2}$$

$$y^*_{3i} = y_{2i}\delta + S_i\theta_3 + X_{3i}\beta_3 + \epsilon_{3i} \tag{3}$$

where the error terms, $(\epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i})$, are assumed to follow a trivariate normal distribution $N(0, \Omega)$ where

$$\Omega = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ & 1 & \rho_{23} \\ & & 1 \end{bmatrix},$$

and ρ_{jk} are parameters capturing the cross-equation correlation. We will test the joint significance of ρ_{jk} using a Wald test to determine our preferred model. We refer to (1)–(3) above as respectively the hospital, ICA and survival equations. The ICA equation includes an interaction term of available capacity and SES, thus allowing for the possibility that capacity constraints may have differential impact on the probability of receiving ICA for different SES groups.

In this specification, SES affects admission to a catheterisation-capable hospital, ICA and survival, and in the latter two equations, directly and indirectly. In the ICA equation, SES directly affects ICA via the parameter θ_2, and indirectly via γ through the hospital equation by affecting admission to catheterisation-capable hospital; Likewise, in the survival equation, SES affects survival directly via θ_3, and indirectly via the

[2]It should be pointed out that we adopt the latent index formulation to describe the unobserved processes that determine the binary outcomes. We do not intend to rationalise this model in a utility-maximising and user choice modelling framework. Given that AMI is an emergency condition and patients are typically rushed to the nearest hospital, user preferences and choice are unlikely to be an important consideration.

ICA equation which in turn is affected directly and indirectly by SES via the hospital equation.

Identification

The identification and estimation of recursive multiple-equation probit models with endogenous dummy regressors have long been controversial. Heckman (1978) and Wilde (2000) suggest that, to the extent that each equation contains at least one varying exogenous regressor, the system can be identified by the functional form and thus needs no exclusion restrictions, provided there is sufficient variation in the data. However, others have argued that such identification will be empirically fragile *a fortiori* due to its heavy reliance on the particular model assumptions, including linear indexing in the latent variables, threshold crossing rules for binary variables and a separable error structure with a prescribed Gaussian distribution (e.g., Jones 2007, p.44).

In view of the ongoing controversy and to reinforce the identification, we rely on exclusion restrictions on top of the functional form. Note that there are two endogenous variables in the system: (i) whether a patient is admitted to a catheterisation capable hospital (y_{1i}) in the ICA equation (2), and (ii) whether a patient receives ICA (y_{2i}) in the survival equation (3). Note also that because of the recursive structure, parameters in the hospital equation (1) are identified without requiring any restrictions. To identify parameters in the ICA and survival equations, we need to impose at the minimum two exclusion restrictions.

First, we specify that Remoteness enters hospital equation (1) but not the ICA equation (2), to identify the coefficient γ in the ICA equation (2). The rationale is that patients living in remote areas generally have to travel a longer distance to a hospital, and there are far fewer catheterisation-capable hospitals outside the metropolitan areas in Australia. However, once patients are admitted to a hospital, remoteness should not be a factor that affects the decision of doctors and hospitals in determining whether the

patient should receive ICA or not.

Second, the variable Catheterisation capacity and its interactions with the SEIFA index and private patient status enter the ICA equation (2) but not the survival equation (3), to identify the coefficient δ in the survival equation (3). We argue that available catheterisation capacity only affects survival via its effects on the probability of receiving ICA; it should not have any direct effects on survival. This is a reasonable assumption since catheterisation capacity is closely tied to the functioning of the catheterisation laboratory, a purpose-built facility for ICA and other catheterisation procedures. Its utilisation has little, if any, correlation to the utilisation and functioning of other departments and facilities in a hospital.

The above exclusion restrictions form the backbone of our identification strategy. In addition, we also specify several other restrictions. A schematic presentation of all the exclusion restrictions is shown in Figure 1.

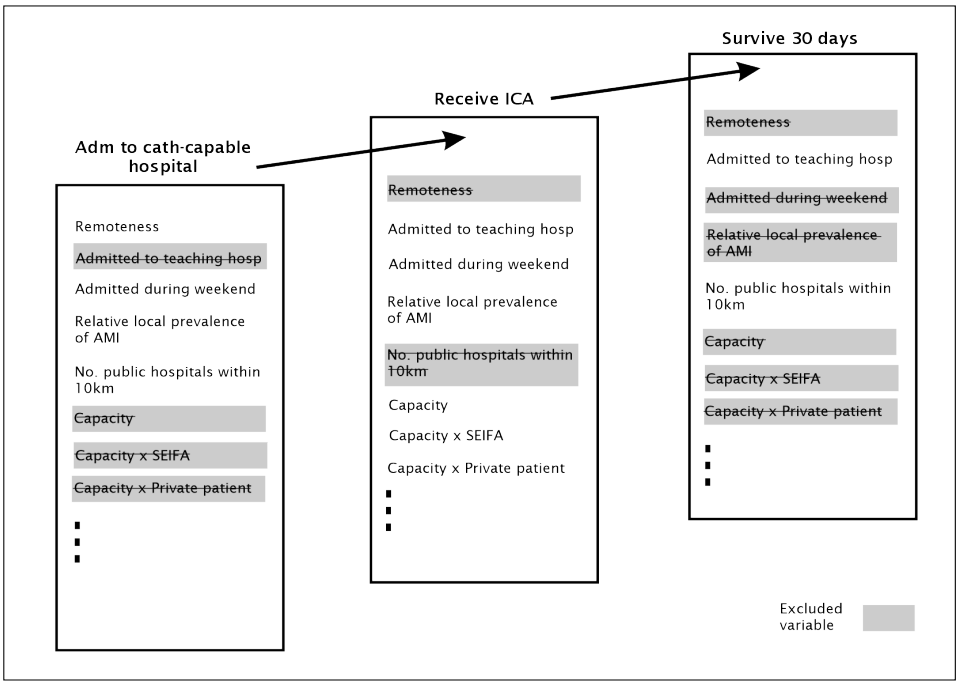


Figure 1: A schematic overview of exclusion restrictions

In particular, based on the evidence that the effects of weekends on AMI mortality

are indirect due to differences in access to care, weekends are found to have no direct mortality effects (Kostis et al., 2007; Fiorentino et al., 2018), we include the Weekend dummy in the hospital equation (1) and ICA equation (2), but not the survival equation (3).

We further argue that the relative local prevalence of AMI during the admission week affects survival through its effects on access to care, by itself the relative local prevalence of AMI has no direct bearing on the survival of an AMI patient. On this basis, we specify that the variable Relative local prevalence of AMI enters the hospital equation (1) and ICA equation (2), but not the survival equation (3).

Another restriction we impose is to exclude the variable Number of public hospitals within 10 kilometre radius from the ICA equation (2), on the basis that this variable is an indicator of options available to patients in an AMI event—a greater number of public hospitals in the area increases the likelihood of finding a catheterisation-capable hospital nearby. This should have no bearing on whether the patient receives ICA or not once the patient has been admitted to a hospital.

We note that the imposition of additional restrictions gives an over-identified system. This means the validity of the additional exclusion restrictions can be formally tested. In our empirical implementation we carry out several over-identification tests and report the results in the Robustness section below.

Catheterisation capacity

To implement the empirical model, a key variable is the short-term available catheterisation capacity faced by a patient admitted on a given day. We do not observe this information, but we observe the number of all catheterisation procedures performed each day. This is a count variable capturing all catheterisation procedures, not just ICA. A catheterisation laboratory typically also performs many other procedures such as angioplasty, pacemaker implants and replacements, etc, in addition to ICA.

Since we observe the number of catheterisation procedures performed at each hospital, we regard the potential capacity of a hospital on any day as the maximum the hospital managed to perform in the past fortnight.[3] AMI is an emergency condition, patients presented with AMI are generally given priority access to the catheterisation laboratory over other patients. Therefore, for a given potential capacity, the available capacity faced by a patient admitted in a given day is simply the difference between the potential capacity and capacity already in use on the day. However, because the time of admission is not observed in the data, the capacity in use is approximated using the average usage of the day and the following day. This averaging is to allow for the possibility that the patient could be admitted late in the day, and hence the following day's capacity usage would apply. This approximation may introduce measurement errors into the capacity calculation, but since the occurrence and timing of AMI are random, we do not expect such measurement errors to be correlated with other covariates in our model.

Formally, we let C_t be the count of catheterisation procedures performed on day t. The short-term potential capacity of the admitting hospital at t is derived as the maximum number of procedures a hospital ever delivered in the past fortnight:

$$C_t^{\max} = \max(C_t, C_{t-1}, \ldots, C_{t-13}).$$

The available capacity faced by patient i admitted at t is the difference between potential capacity and capacity in use:

$$\tilde{A}_i = C_t^{\max} - (C_t + C_{t+1})/2,$$

where capacity in use at t is approximated as the average number of performed on days t and $t+1$.

In the empirical implementation, we allow for nonlinear effects of available capacity by

[3]Instead of the past fortnight, we also use the maximum in the previous 7 and 30 days as robustness checks. We do not find any notable differences in the results. A summary of our results is available upon request.

defining a categorical variable as follows:

$$A_i = \begin{cases} \text{Very low} & \text{if } \tilde{A}_i \leq 1.5, \\ \text{Low} & \text{if } 1.5 < \tilde{A}_i \leq 3.5, \\ \text{Medium} & \text{if } 3.5 < \tilde{A}_i \leq 6.5, \\ \text{High} & \text{if } \tilde{A}_i > 6.5. \end{cases}$$

The cut-off values of 1.5, 3.5, and 6.5 correspond to the 25th, 50th, and 75th percentiles of the sample values of $\tilde{A}_i$.

Estimation

We estimate the system of three equations (1)–(3) using the user-written command *Conditional (recursive) mixed-process (cmp)* in Stata (Roodman, 2011). The calculation of the cumulative joint normal distribution is via simulation using the Geweke-Hajivassiliou-Keane (ghk) algorithm (Gates, 2006).

The quantities of interest are the total, direct and indirect marginal effects of a given SES measure, s_i, on an outcome, for instance, survival (y_{3i}). Assume s_i appears in all three equations (1), (2) and (3), respectively denoted by s_{1i}, s_{2i} and s_{3i}. The total effect is given by

$$\begin{aligned} \frac{\partial E\left(y_{3i}|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_i} =& \frac{\partial E\left(y_{3i}|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{3i}} + \frac{\partial E\left(y_{3i}|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{2i}} \\ &+ \frac{\partial E\left(y_{3i}|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{1i}}. \end{aligned}$$

The direct effect therein is:

$$\frac{\partial E\left(y_{3i}|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{3i}},$$

where $X_i = X_{1i} \cup X_{2i} \cup X_{3i}$. We derive the algebraic expressions for total, direct and indirect effects in *Appendix A*.

We are also interested in the marginal effects of available capacity, and its interactions with SES. Note that available capacity only enters the ICA equation, there are only direct

effects in relation to available capacity on this equation. For the survival equation, there will only be indirect effects since available capacity is assumed to have no direct effect on survival.

The partial effects of SES interacting with available capacity are of particular interest. We are interested in comparing the partial effect of SES on ICA when available capacity is low, i.e., when capacity could be constrained such that rationing is more likely to occur, with situations when available capacity is high, i.e., when there is no capacity constraint and rationing is unlikely. For a given SES measure, s_i, we denote $\Delta_{s_i|A_i}$ as its partial effect at specific capacity level, a. That is,

$$\Delta_{s_i|A_i} \equiv \left. \frac{\partial E\left(y_{2i}|y_{1i}, S_i, X_{2i}, A_i\right)}{\partial s_i} \right|_{A_i=a},$$

where a ranges from 'very low' to 'high.'

3 Data

We made use of hospital administrative data from the state of Victoria, Australia. The main data were extracted from two datasets—the Victorian Admitted Episodes Dataset (VAED) and Victorian Emergency Minimum Dataset (VEMD). The data cover a seven-year period, 2004/05–2010/11. The datasets were maintained by the Victorian Department of Health and Human Services (DHHS), which manages public hospitals in the state and also in charge of regulating private hospitals in matters such as patient safety. The data were linked to the death registry records by DHHS to obtain the date of death for deceased patients.

The population of our study consisted of all patients admitted to hospitals with a diagnosis of STEMI or NSTEMI who had no prior AMI admissions in the previous five years. Patients experiencing prior AMI episodes in the previous five years were excluded since their case complexity and survival rates are very different from those with no prior AMI history. Identification of STEMI and NSTEMI was via the International Statisti-

cal Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification (ICD-10-AM), which is an expanded version of the World Health Organization's ICD-10 codes. A hospital episode can include ED presentations and hospital admissions associated with an AMI; episodes up to 24 hours between separations and admissions were included in the same AMI hospital admission episode. For episodes where multiple hospitals were involved, admission to catheterisation capable hospitals, access to ICA, and the subsequent survival outcome were attributed to the hospital of first admission. This is because, due to the urgent nature of AMI, the first few hours are of critical importance for administering the appropriate treatment. This means hospitals treating the patient in the first admission should be responsible for making the right treatment decisions.

We further exclude patients who underwent ICA or PCI in the previous 12 months ($n = 9,322$), and patients younger than 35 or older than 90 ($n = 4,541$). These patients are excluded because they tend to have very different risk profile and case complexity, as such their probabilities of ICA and survival are likely to be different from those of other patients.

After applying the exclusion restrictions, we obtained a sample comprising 13,468 STEMI and 42,167 NSTEMI admissions over the sample period. The admission episodes occurred in 144 hospitals, of which 47 were private hospitals. Not all hospitals were catheterisation capable, which we define as hospitals that could perform at least 80 catheterisation procedures a year.[4] Of the 144 hospitals in the sample, 32 were catheterisation capable, 19 of which were private hospitals. Note that an AMI patient may be admitted in a non-catheterisation capable hospital (perhaps because it was the nearest hospital), be assessed and stabilised as necessary and transferred to a catheterisation capable hospital to undergo ICA and further treatment. In this case the access to ICA and outcomes were attributed to the admitting hospital.

[4]We determine this criterion of 80 procedures a year by consulting with a senior cardiologist working in a major public hospital in Victoria. The criterion translates to about 1.5 procedures per week, which although arbitrary, is generally agreed as a credible indicator of catheterisation capability.

Most variables were constructed in a straightforward manner. For the three SES measures we use, (i) remoteness was classified into three categories (major cities, inner regional and outer regional areas); (ii) SEIFA is a suite of composite indices published by the ABS, which map to the Statistical Local Area (SLA) of a patient's residence (a SLA is a geographical classification unit defined by the ABS for the purpose of data collection; see ABS, 2006). It comprises four different indices. The specific index used here is the Index of Relative Socio-Economic Disadvantage. For the estimation, areas were categorised into quintiles based on the index. Patients in the first quintile are the most disadvantaged while those in the fifth are the most advantaged; and (iii) private patient status, which is constructed as a binary variable indicating whether the patient was admitted as a private or public patient.

A variable that requires further explanation is 'Relative local prevalence of AMI during admission week', which was constructed to capture demand shocks in local areas. The count of AMI for each week was obtained for each SLA in the state. Next, the week with the highest count of AMI during the quarter of each year was identified. This represented the busiest week for hospitals in the SLA in attending to AMI patients. For a patient with AMI admitted during a specific week, we measured the relative prevalence of AMI by taking the ratio of the total count of AMI in that week to the busiest week in the quarter. A higher ratio indicates hospitals in the SLA were more likely to face capacity pressure and thus less likely for a patient to get admitted to a catheterisation-capable hospital.

4 Results

Summary statistics

We present some summary statistics about the sample in Table 1. For the outcomes of interest, we see that most patients managed to get admitted to catheterisation capable

hospitals—about 90 per cent for STEMI and 82 per cent for NSTEMI patients. The rate of ICA differed between STEMI (74 per cent) and NSTEMI (40.4 per cent), likely a reflection of the greater urgency of the former. The survival rate 30 days post discharge was slightly lower for STEMI at 88.4 per cent, compared to 90.8 per cent for NSTEMI patients.

In terms of demographic characteristics, there were more male than female patients, STEMI patients were slightly younger than NSTEMI patients—the average age of patients was 66 years for STEMI and 73 years for NSTEMI. The majority of patients were married, and Australian born. NSTEMI patients had more other complex medical conditions than STEMI patients, as reflected in the higher average Charlson comorbidity score of STEMI patients. Slightly above half of all patients arrived by ambulance, and about a quarter of all patients were admitted during weekends. About 36 per cent of STEMI patients were admitted to a teaching hospital, compared to about 29 per cent of NSTEMI patients. For STEMI patients, about 22 per cent of admissions occurred when the available catheterisation capacity was at very low level, 22 per cent at low, 30 per cent at medium, and the remaining 27 per cent at high capacity level. The corresponding percentages for NSTEMI patients were 28, 21, 27, and 23 per cent. Not surprisingly, given the geographic concentration of Australia's population, most patients (75 per cent or more) resided in major cities, and only about 6 per cent resided in outer regional or remote areas. A significant proportion of AMI patients were admitted as private patients—about 35 per cent of STEMI patients and 31 per cent of NSTEMI patients.

Total, indirect and direct effects

We estimate the system of probit equations separately for STEMI and NSTEMI patients. We first did the estimation without imposing any constraints on the cross-equation correlation structure of the errors, and then test the correlation structure using the Wald test. Note that the likelihood ratio test does not apply here due to the clustering

Table 1: Summary statistics, STEMI and NSTEMI patients

	STEMI		NSTEMI	
	Mean	s.d.	Mean	s.d.
Admitted to cath-capable hosp	0.895	0.306	0.819	0.385
ICA	0.740	0.439	0.404	0.491
Survived 30 days post discharge	0.884	0.320	0.908	0.289
Gender (Male = 1)	0.698	0.459	0.586	0.493
Age	66.297	13.639	72.997	12.566
Married	0.628	0.483	0.563	0.496
Australian born	0.591	0.492	0.559	0.496
Charlson comorbidity score	1.154	0.423	1.346	0.595
Arrival by ambulance	0.520	0.500	0.541	0.498
No. of hospitals within 10KM	4.598	5.009	4.911	5.165
Relative local prevalence of AMI	0.692	0.278	0.685	0.277
Teaching hospital	0.356	0.479	0.292	0.455
Admitted during weekends	0.264	0.441	0.253	0.434
Available cath capacity cat.				
Very low	0.217	0.412	0.283	0.451
Low	0.218	0.413	0.212	0.408
Medium	0.297	0.457	0.272	0.445
High	0.268	0.443	0.233	0.423
SEIFA disadv quintile				
1st	0.149	0.356	0.161	0.367
2nd	0.217	0.412	0.219	0.413
3rd	0.159	0.365	0.156	0.363
4th	0.287	0.452	0.272	0.445
5th	0.188	0.391	0.193	0.394
Remoteness				
Major cities	0.750	0.433	0.761	0.426
Inner regional areas	0.192	0.394	0.181	0.385
Outer regional areas	0.059	0.235	0.057	0.232
Private patient	0.350	0.477	0.305	0.460
No. admissions	13,468		42,167	

of standard errors. The Wald test produced Chi-square test statistics (with 3 degrees of freedom) of 18.63 ($p < 0.001$) and 3.99 ($p = 0.263$) for respectively STEMI and NSTEMI. We therefore reject the null hypothesis of uncorrelated errors for STEMI but not for NSTEMI patients. Based on the test results, we chose our preferred specification as correlated errors for STEMI and uncorrelated errors, i.e., independent probit equations for NSTEMI.

After estimating our preferred specifications, we obtain estimates of marginal effects of SES on the probabilities of admission to catheterisation capable hospitals, ICA, and 30-day survival. Table 2 shows, for STEMI and NSTEMI patients, the estimated total effects of the three SES variables. The total effects are decomposed into direct and indirect effects in Table 3. A complete listing of coefficient estimates and standard errors can be found in *Appendix B*.

The results in Table 2 show that remoteness has a significant and large effect on the probability of patients being admitted to catheterisation capable hospitals. Compared to patients in major cities, STEMI patients in inner regional areas were 13.6 percentage points less likely to be admitted to a catheterisation capable hospital, while those in outer regional areas were 25.3 percentage points less likely. The corresponding effects on NSTEMI patients were even larger, at 21.9 and 36.2 percentage points for respectively patients in inner regional and outer regional areas. Unlike remoteness, SEIFA has no significant effects on the probability of being admitted to catheterisation capable hospitals for either STEMI or NSTEMI patients. Compared to public patients, private patients appeared to have a greater likelihood of gaining admission to a catheterisation-capable hospital, the difference is 6.2 percentage points for STEMI and 7.9 percentage points for NSTEMI patients.

For both STEMI and NSTEMI patients, the probability of receiving ICA is significantly affected by remoteness and private patient status, and by SEIFA for STEMI but not NSTEMI patients. Note that remoteness does not directly enter the ICA equation

(2), and thus the estimated total effects consist entirely of the indirect effects via the hospital equation (1). STEMI patients in inner regional and outer regional areas were respectively 11.0 and 21.5 percentage points less likely to receive ICA than patients in major cities. The corresponding probabilities for NSTEMI patients were 8.8 and 15.4 percentage points lower.

Table 2: Total effects of SES on STEMI and NSTEMI patients

	Admit to cath-capable hospital		Receive ICA		30-day Survival	
	y_1	p-val	y_2	p-val	y_3	p-val
STEMI						
Remoteness (v major cities)						
Inner regional	-0.136*	0.014	-0.110*	0.013	-0.015	0.115
(s.e.)	(0.055)		(0.044)		(0.010)	
Outer regional	-0.253***	<0.001	-0.215***	<0.001	-0.026*	0.033
(s.e.)	(0.073)		(0.060)		(0.012)	
SEIFA quintile (v 1st)						
2nd quintile	0.013	0.630	0.044†	0.054	0.004	0.655
(s.e.)	(0.027)		(0.023)		(0.010)	
3rd quintile	0.013	0.691	0.033	0.222	0.005	0.633
(s.e.)	(0.033)		(0.027)		(0.010)	
4th quintile	0.026	0.449	0.072*	0.041	0.011	0.211
(s.e.)	(0.034)		(0.035)		(0.009)	
5th quintile	0.025	0.412	0.072*	0.019	0.003	0.777
(s.e.)	(0.031)		(0.031)		(0.011)	
Private patient (v public)	0.062**	0.006	0.117***	<0.001	0.055***	<0.001
(s.e.)	(0.023)		(0.023)		(0.006)	
NSTEMI						
Remoteness (v major cities)						
Inner regional	-0.219*	0.025	-0.088*	0.028	-0.003	0.573
(s.e.)	(0.098)		(0.040)		(0.006)	
Outer regional	-0.362***	<0.001	-0.154***	<0.001	-0.004	0.601
(s.e.)	(0.094)		(0.041)		(0.008)	
SEIFA quintile (v 1st)						
2nd quintile	-0.021	0.613	0.038	0.153	-0.003	0.725
(s.e.)	(0.041)		(0.027)		(0.008)	
3rd quintile	-0.003	0.954	0.034	0.265	0.009	0.199
(s.e.)	(0.048)		(0.030)		(0.007)	
4th quintile	-0.052	0.451	0.036	0.370	-0.003	0.707
(s.e.)	(0.069)		(0.040)		(0.008)	
5th quintile	-0.053	0.378	0.040	0.300	-0.004	0.678
(s.e.)	(0.060)		(0.039)		(0.010)	
Private patient (v public)	0.079*	0.015	0.131***	<0.001	0.014***	<0.001
(s.e.)	(0.032)		(0.028)		(0.003)	

Notes: Standard errors obtained via delta method.
Significance levels: †: 10% *: 5% **: 1% ***: 0.1%

Having private insurance not only increases the likelihood of geting admitted to catheterisation-capable hospitals but also increases one's likelihood of receiving ICA. The advantage over public patients was respectively 11.7 and 13.1 percentage points higher for private STEMI and NSTEMI patients. Being in higher (i.e., advantageous) SEIFA quintiles appear to increase the likelihood of receiving ICA for STEMI patients but no statistically significant difference was found for NSTEMI patients. STEMI patients in the 4th and 5th quintiles were on average 7.2 percentage points more likely to receive ICA, compared to those in the lowest quintile.

The probability of survival 30 days post discharge was significantly affected by private patient status for both STEMI and NSTEMI patients, and for STEMI patients, remoteness also played a role; the probability did not appear to vary significantly by SEIFA quintile for both groups of patients. Compared to public patients, those admitted as private patients have a higher probability of survival, by about 5.5 and 1.4 percentage points for respectively STEMI and NSTEMI patients. STEMI patients in outer regional areas were less likely to survive than patients in major cities—the probability is lower by 2.6 percentage points. It is worth noting that the effect of remoteness on survival is the combination of its direct and indirect effects, where the indirect effect is via the ICA equation (2) whose remoteness effects are in turn indirect via the hospital equation (1).

The total effects shown in Table 2 are decomposed into direct and indirect effects in Table 3. Note that the hospital equation is omitted here since there are no indirect effects, all effects are by construction direct for this equation. Further, as noted before, the effects of remoteness on receiving ICA are also entirely indirect via the hospital equation.

The results show that, on the probability of receiving ICA, the effects are more direct than indirect, whereas there does not appear to be any clear tendency on survival. Notably the effects of private patient status on the probability of receiving ICA are predominantly working through the direct effect. For STEMI patients, the direct effect

was highly statistically significant and at 7.0 percentage points, compared to the indirect effect of 4.8 percentage points. The contrast is even larger for NSTEMI patients the direct effect was 9.7 percentage points, compared to the indirect effect of 3.4 percentage points.

Compared to those in the first quintile of SEIFA, patients in the fourth and fifth quintiles were more likely to receive ICA, with the direct effects dominating the indirect effects. For STEMI patients, the direct effects were around 5 percentage points, while the indirect effects were less than half of those of indirect effects and not statistically significant. Similarly, for NSTEMI patients, the direct effects were similarly about 6–7 percentage points, and the indirect effects were not statistically significant.

We next turn to the estimated effects of the SES measures on survival. It is worth noting that the indirect effects are the cumulative effects via admission to catheterisation hospitals and receiving ICA. Private patient status appears to have a large and significant direct effect on survival for STEMI patients, at 4.7 percentage points, compared to the indirect effect of 0.8 percentage point which is statistically insignificant. For NSTEMI patients, the direct effect of private patient status was small and not statistically significant, whereas the indirect effect was 1.0 percentage points and significant. Remoteness appears to have a negative effect on the survival of AMI patients. For STEMI patients neither its direct nor indirect effects are statistically significant, although their combined effect, as shown in Table 2 above, is statistically significant. For NSTEMI patients, the indirect effects of Remoteness are statistically significant, but not the direct effects. We note that the magnitude of indirect effects are comparable for STEMI and NSTEMI patients, suggesting that both groups faced similar access disadvantage, although only the effects on NSTEMI patients are statistically significant. Lastly, the results show that SEIFA did not appear to have any statistically significant direct or indirect effects on survival for either STEMI and NSTEMI patients.

We next examine the estimated effects of available ICA capacity, as capacity constraints

Table 3: Direct and indirect effects of SES, STEMI and NSTEMI patients

	Receive ICA (y_2)				Survival (y_3)			
	Indirect (fr y_1)		Direct		Indirect (fr y_1 & y_2)		Direct	
	M.E.	p-val	M.E.	p-val	M.E.	p-val	M.E.	p-val
STEMI								
Remoteness (v major cities)								
Inner regional	-0.110*	0.013	–		-0.006	0.312	-0.009	0.464
(s.e.)	(0.044)				(0.006)		(0.012)	
Outer regional	-0.215***	<0.001	–		-0.012	0.266	-0.014	0.390
(s.e.)	(0.060)				(0.011)		(0.016)	
SEIFA quintile (v 1st)								
2nd quintile	0.009	0.618	0.035†	0.080	0.003	0.348	0.001	0.932
(s.e.)	(0.018)		(0.020)		(0.004)		(0.011)	
3rd quintile	0.009	0.683	0.023	0.182	0.002	0.397	0.002	0.830
(s.e.)	(0.023)		(0.018)		(0.003)		(0.010)	
4th quintile	0.020	0.427	0.052*	0.022	0.005	0.338	0.006	0.590
(s.e.)	(0.025)		(0.023)		(0.006)		(0.011)	
5th quintile	0.019	0.374	0.053**	0.010	0.006	0.315	-0.003	0.827
(s.e.)	(0.022)		(0.021)		(0.006)		(0.012)	
Private (v public) patient	0.048**	0.008	0.070***	< 0.001	0.008	0.248	0.047***	< 0.001
(s.e.)	(0.018)		(0.014)		(0.007)		(0.009)	
NSTEMI								
Remoteness (v major cities)								
Inner regional	-0.088*	0.028	–		-0.006*	0.028	0.002	0.627
(s.e.)	(0.040)				(0.003)		(0.005)	
Outer regional	-0.154***	<0.001	–		-0.009***	<0.001	0.005	0.413
(s.e.)	(0.041)				(0.003)		(0.006)	
SEIFA quintile (v 1st)								
2nd quintile	-0.010	0.628	0.048*	0.028	0.003	0.117	-0.006	0.392
(s.e.)	(0.020)		(0.022)		(0.002)		(0.007)	
3rd quintile	-0.001	0.955	0.035†	0.083	0.003	0.228	0.006	0.360
(s.e.)	(0.023)		(0.020)		(0.002)		(0.007)	
4th quintile	-0.025	0.471	0.061**	0.006	0.003	0.279	-0.007	0.416
(s.e.)	(0.034)		(0.022)		(0.003)		(0.008)	
5th quintile	-0.027	0.410	0.068**	0.001	0.004	0.221	-0.008	0.388
(s.e.)	(0.033)		(0.021)		(0.003)		(0.009)	
Private (v public) patient	0.034*	0.019	0.097***	< 0.001	0.010***	< 0.001	0.004	0.173
(s.e.)	(0.015)		(0.020)		(0.002)		(0.003)	

Notes: Standard errors obtained via delta method.
Significance levels: †: 10% *: 5% **: 1% ***: 0.1%

could cause rationing which may adversely affect survival. Recall that capacity only enters the ICA equation but not the other equations, and thus the estimated effects in Table 4 show only direct effects on ICA and indirect effects on survival. The estimates suggest that, as capacity rises with reference to the base category of 'very low' available capacity, both ICA and survival probabilities rise, although the increases are not statistically significant.

Table 4: Marginal effects of available capacity, STEMI and NSTEMI

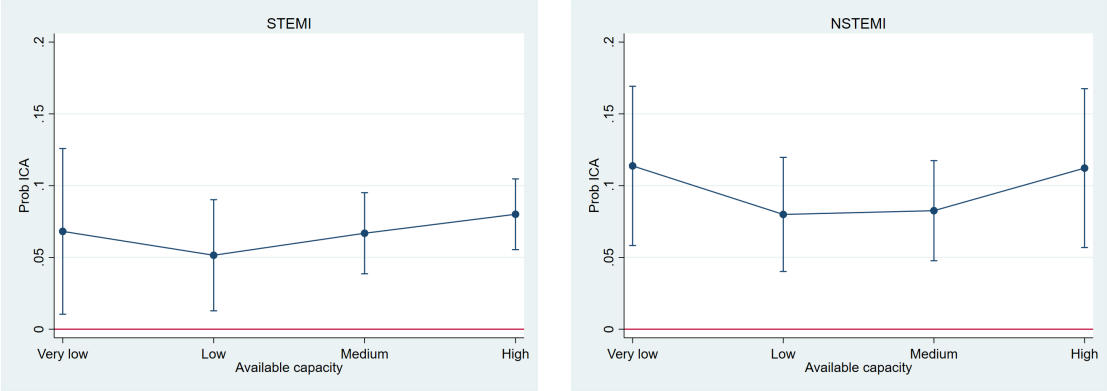
	Receiving ICA (y_2)		Survival (y_3)	
	Direct		Indirect (from y_2)	
	M.E.	p-val	M.E.	p-val
STEMI				
Available capacity (v Very low)				
Low	0.011	0.466	0.001	0.529
	(0.016)		(0.001)	
Medium	0.024	0.347	0.002	0.400
	(0.025)		(0.002)	
High	0.032	0.232	0.003	0.326
	(0.027)		(0.003)	
NSTEMI				
Available capacity (v Very low)				
Low	0.023	0.184	0.002	0.195
	(0.017)		(0.001)	
Medium	0.028	0.333	0.002	0.358
	(0.029)		(0.002)	
High	0.028	0.380	0.002	0.395
	(0.032)		(0.003)	

Note: Standard errors obtained via delta method.

Although available capacity has no significant effects on ICA and survival, its interactions with SES variables show a pattern that suggests inequity in access to ICA. Figures 2 and 3 show the partial effect estimates at different levels of available capacity of respectively private patient status and SEIFA. In Figure 2, both Figures 2(a) and 2(b) show that the probability of ICA access between private and public patients has a gap across all capacity levels, and the access gap is larger for NSTEMI than STEMI patients, possibly due to the more urgent nature of STEMI.

Figure 3 shows that ICA access varies between patients in different SEIFA quintiles

at different capacity levels. When the available capacity is 'very low', the difference in probability of receiving ICA between the first and fifth quintiles is about 0.2 for STEMI and 0.15 for NSTEMI patients in favour of the advantaged group, and both are statistically significant at 5% level. The gap narrows and becomes statistically insignificant as capacity rises from 'very low' to 'low' and beyond. Importantly, the gaps are narrower for patients in the second, third and fourth quintiles, and not statistically different from zero, except in a couple of instances for patients in the third quintile.

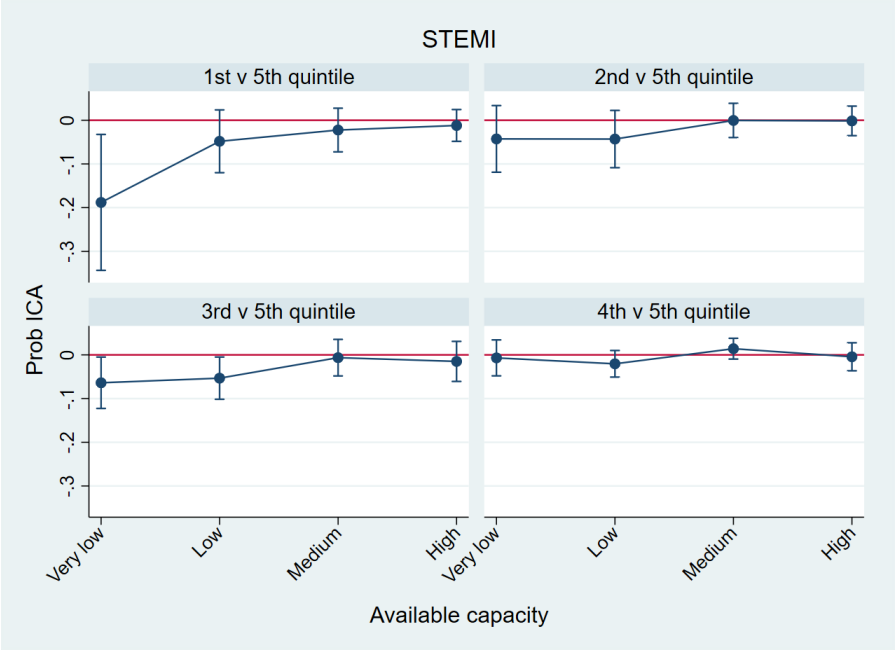


(a) STEMI (b) NSTEMI

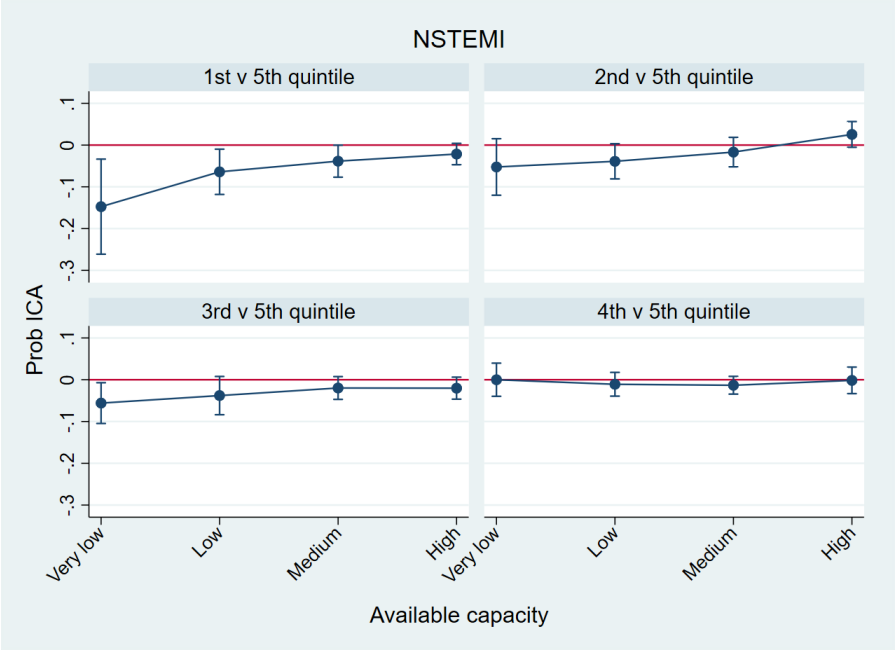
Figure 2: Partial effects ($\Delta_{s_j|A_i}$), private patient status and available capacity on ICA

5 Robustness

We examine the robustness of our results from three different angles. We first estimate an alternative specification with the least number of exclusion restrictions. Our second robustness check is to exploit the over-identified specification of our base model to conduct a series of over-identification tests. The third is using an alternative functional form specification in the form of the linear probability model (LPM). In all cases our results are robust to the alternative specifications.



(a) STEMI



(b) NSTEMI

Figure 3: Partial effects ($\Delta_{s_j|A_i}$), SEIFA and available capacity on ICA

Model with least number of exclusion restrictions

Recall that, to identify the recursive system of probit equations (1)–(3), we require at the minimum two exclusion restrictions (on top of the functional form identification of probit). That is, one variable in the hospital equation (1) is to be excluded from the ICA equation (2), and another variable in the ICA equation (2) must not appear in the survival equation (3). For this robustness check, we estimate just such a system using respectively remoteness and catheterisation capacity as the two excluded variables. We call this the just-identified probit model, although strictly speaking this 'just-identified' description is only true for linear models.

We present the results on total, direct and indirect effect estimates of SES on access to catheterisation hospitals, receiving ICA, and eventual survival 30 days post discharge in Appendix C (Table C1 and C2). From the results, we find no change in the sign or statistical significance of any of the estimated effects. Moreover, very similar effect size estimates are reported with respect to access to catheterisation hospitals and receiving ICA. Some variation in effect size is found in relation to survival 30 days post discharge, but their sign and statistical significance remain unchanged. Our overall conclusions remain unchanged with the estimates from the just-identified model—private patient status and remoteness affect access to care and have significant direct and indirect effects on survival.

Over-identification tests

Since our base model is over-identified, i.e., having more exclusion restrictions than the minimum required to identify the two endogenous variables, we can test the validity of the additional exclusion restrictions. In particular, we test our base model against the just-identified model discussed above through a series of over-identification tests. The tests examine whether: (i) the Weekend dummy should enter the survival equation (3); (ii) the Relative local prevalence of AMI should enter the survival equation (3); and (iii)

the Number of public hospitals within 10 kilometer radius should enter the ICA equation (2). For ease of reference, we denote the parameters of these variables as respectively α_1, α_2 and α_3.

Notwithstanding the extensive literature available on over-identification tests for linear models, there is a dearth of econometric results in relation to tests specifically designed for models with discrete outcomes. In a similar spirit to the Refutability test described in Guevara (2018), we conduct a simple test to jointly test the three additional exclusion restrictions as follows. In essence, we regard the just-identified model, which has the least number of exclusion restrictions, as an augmented version of our base model, or put differently, our base model is nested within the just-identified model. The null hypothesis of the test is: $H_0 : \alpha_1 = 0, \alpha_2 = 0, \alpha_3 = 0$. In addition to testing all three restrictions as a joint test, we also test them in pairwise combinations and individually. For each test, a different augmented model is separately estimated for STEMI and NSTEMI patients. The Wald test is used due to the presence of clustered standard errors. The test results are summarised in Table 5, which shows that the null hypothesis cannot be rejected in any of the 14 tests. The test results lend support to the validity of the additional exclusion restrictions imposed in our base model.

Linear probability model

Our final robustness check is to estimate a system of recursive linear equations in the form of LPM. The specification is exactly the same as our base model except the functional form is linear instead of probit. The advantages of LPM are its simplicity and that its estimation does not require distributional assumptions. However, a key disadvantage of LPM is it does not confine probabilities to within $[0, 1]$. After estimating the LPM model, we compute the total, direct and indirect effects and report the results in Appendix C (Tables C3 and C4). Comparing with our base model, LPM produces very similar results on total, direct and indirect effects of SES, except that its effect sizes are generally a

Table 5: Over-identification test results, STEMI and NSTEMI patients

	STEMI	NSTEMI
$H_0 : \alpha_1 = 0, \alpha_2 = 0, \alpha_3 = 0$		
χ^2	3.42	1.31
p-value	0.331	0.728
$H_0 : \alpha_1 = 0, \alpha_2 = 0$		
χ^2	0.68	1.15
p-value	0.713	0.564
$H_0 : \alpha_2 = 0, \alpha_3 = 0$		
χ^2	2.12	0.68
p-value	0.346	0.712
$H_0 : \alpha_1 = 0, \alpha_3 = 0$		
χ^2	3.37	0.96
p-value	0.185	0.619
$H_0 : \alpha_1 = 0$		
χ^2	2.09	0.02
p-value	0.148	0.898
$H_0 : \alpha_2 = 0$		
χ^2	0.02	0.45
p-value	0.895	0.501
$H_0 : \alpha_3 = 0$		
χ^2	1.83	0.28
p-value	0.176	0.599

little larger, resulting in slightly more estimated effects that are statistically significant. The larger effect size is likely resulting from the LPM feature that does not restrict the probability of modelled events to fall within 0 and 1. For this and other reasons, LPM is becoming less frequently used for modelling discrete outcomes (Greene, 2012). Nonetheless, for our purposes, the LPM results indicate that our results are robust to the probit model assumptions.

6 Discussion

By estimating a recursive system of equations, we disentangle the direct and indirect effects of SES on survival of AMI patients. The indirect effects work through access to care, first through attending a catheterisation capable hospital and second by receiving ICA. We do not consider these differences in access and outcomes to reflect personal preferences, since in the context of AMI, care needs are urgent and the clinical guidelines for ICA are well established. Personal preferences such as whether to receive care or how much care is preferred have less relevance in this situation.

Our results underscore the importance of accounting for indirect effects in assessing the impact of SES on outcomes of AMI patients. In many instances we see that indirect effects have significant and material impacts on access and survival of AMI patients, e.g., the indirect effects of remoteness on the likelihood of receiving ICA and survival for NSTEMI patients.

Remoteness is found to be key in affecting admissions to catheterisation hospitals, which have large indirect effects on access to ICA, and could in turn affect survival. The result highlights the importance of getting to a catheterisation capable hospital for AMI patients. Those in regional and remote areas are more likely to be admitted to non-catheterisation hospitals and transferred later. They may have missed the ideal window for ICA, which could have adversely affected survival.

Private patient status turns out to be a highly relevant factor affecting ICA access and survival for AMI patients. It has large direct effects on being admitted to catheterisation-capable hospitals and receiving ICA, which in turn affects survival. This result likely reflects the wider access by patients with private health insurance who can access both private and public hospitals with catheterisation facilities. Wider access has in turn enhanced the survival of private patients. This indirect effect of private patient status on survival via wider access is relatively large for NSTEMI patients and statistically significant. The direct effect of private patient status on survival is likely a reflection of income or wealth, since wealthier individuals are overwhelmingly more likely to purchase private health insurance in Australia (Palangkaraya and Yong, 2005).

Even though the total effects of SEIFA index quintiles are mostly statistically insignificant, its direct effects on receiving ICA show that patients in the fifth quintile were more likely to receive ICA than those in the first quintile for both STEMI and NSTEMI patients. The difference in access by SEIFA, however, did not appear to impact the survival of both STEMI and NSTEMI patients.

Taken together, our results show that both direct and indirect effects are important in affecting the access to ICA and the subsequent survival of AMI patients. These results suggest that while improving the access to ICA (and other cardiac procedures) is important, to substantially improve the survival of disadvantaged AMI patients, the direct effects of low SES (e.g., perhaps because of lack of education and low awareness) must also be addressed. Several reasons may account for the higher survival probability of high SES patients, including their generally better health, and their ability to comply with treatment recommendations (Tang et al., 2013; Hagen et al., 2015).

It is noteworthy that although available catheterisation capacity has no significant effects on access to ICA or subsequent survival, its interactions with SES show that the most disadvantaged patients have lower access to ICA. In particular, its interaction with SEIFA show that access to ICA tends to disadvantage patients in the lowest SEIFA

quintile when available capacity is limited, i.e., when rationing may become necessary. As capacity rises the access gap narrows and generally disappears. Also notable is that the gaps between other SEIFA quintiles (versus the most advantaged) are not as wide and in most instances not statistically significant. The result shows that even though there is no access inequity for the system as a whole with regard to the impact of catheterisation capacity, inequity can still arise in situations where capacity is constrained and rationing is likely. This may arise as a result of implicit triage rules applied by hospital staff and clinicians to allocate limited capacity to maximise the overall survival of all patients, as suggested by Hagen et al. (2015) in their theory model. Notably, Li et al. (2013) found similar results on the use of cardiac revascularization procedures in the U.S. by interacting hospital capacity with race, and concluded that racial disparities between whites and blacks worsened in small-capacity hospitals.

7 Concluding Remarks

We jointly model the probabilities of admission to a catheterisation capable hospital, receipt of ICA, and survival 30-days post discharge for AMI patients using a three-equation recursive system of probit equations. We examine the direct and indirect effects of SES, which we measure using remoteness of residence, private patient status, and a small area index of socioeconomic status known as SEIFA.

The results suggest that in Australia, which has a universal health care system, access to care by socioeconomically disadvantaged AMI patients is still lower than non-disadvantaged patients. The lower access can adversely affect survival through its indirect effects, which are in addition to the direct effects of being in a disadvantaged group. We further show that the level of available catheterisation capacity has little effect on ICA access on average across all SES groups. However, when interacting with SES variables, we find that in situations of limited capacity where rationing is likely, ICA access by disadvantaged patients appears to be impacted more than that of non-

disadvantaged patients. This finding suggests that access to care can be inequitable in situations when the system is capacity-constrained, even though no access inequity is found when capacity is non-constrained.

Our findings suggest that public policy to reduce inequality in health should not only improve access difficulties faced by the disadvantaged, but also address the direct effects of SES in order to more effectively bridge the outcomes between the disadvantaged and advantaged groups.

This study has several limitations. The administrative data we use did not contain any information on health habits and behaviours such as smoking, exercise and diets, which are known to differ by SES and are highly relevant risk factors not only affects cardiovascular disease risks but also outcomes following cardiovascular events. Our data also did not contain precise timing of admission and ICA, as such we are unable to determine the amount of elapsed time to ICA following admission. Lastly, we have no information on ambulance wait times or travel delays before admission. This information is particularly important for further investigations of the extent of access barriers facing patients in remote areas in comparison to those living in cities.

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Appendix A Expressions for Total, Direct and Indirect Effects

Let $y_{1i}^*, y_{2i}^*, y_{3i}^*$ be three latent variables which are the underlying continuous variables determining whether patient i is, respectively, admitted to a catheterisation-capable hospital, receiving ICA, or surviving 30 days post discharge.

Corresponding to y_{ji}^* is the observed binary outcome:

$$y_{ji} = \begin{cases} 1 & \text{if } y_{ji}^* > 0; \\ 0 & \text{otherwise.} \end{cases}$$

where $j = 1, 2, 3$.

Let S_i be a vector of SES variables, A_i is a scalar denoting available catheterisation capacity and X_{1i}, X_{2i}, X_{3i} denote vectors of other explanatory variables. We specify a recursive system of three probit equations as:

$$y_{1i}^* = S_i\theta_1 + X_{1i}\beta_1 + \epsilon_{1i} \tag{A4}$$
$$y_{2i}^* = y_{1i}\gamma + S_i\theta_2 + \alpha A_i + A_i \times S_i\lambda + X_{2i}\beta_2 + \epsilon_{2i} \tag{A5}$$
$$y_{3i}^* = y_{2i}\delta + S_i\theta_3 + X_{3i}\beta_3 + \epsilon_{3i}, \tag{A6}$$

where $(\epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i}) \sim N(0, \Omega)$,

$$\Omega = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ & 1 & \rho_{23} \\ & & 1 \end{bmatrix}$$

Without loss of generality, assume a given SES variable, $s_i \in S_i$, enters into all three equations (A4)–(A6), respectively denoted by s_{1i}, s_{2i} and s_{3i}. The *total effect* of s_i on survival y_{3i} consists of the *direct effect* of s_{3i} on the survival of patient i by eq. (A6) and the *indirect effect* operating through s_{2i}'s effect on receiving ICA (via eq. (A5)) and s_{1i}'s effect on admission to a catheterisation-capable hospital (via eq. (A4)). We derive below the expression for the total effect.

$$\begin{aligned} \frac{\partial E\left(y_{3i}|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_i} =& \frac{\partial E\left(y_{3i}|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{3i}} + \frac{\partial E\left(y_{3i}|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{2i}} \\ &+ \frac{\partial E\left(y_{3i}|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{1i}} \\ =& \frac{\partial P\left(y_{3i}=1|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{3i}} + \frac{\partial P\left(y_{3i}=1|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{2i}} \\ &+ \frac{\partial P\left(y_{3i}=1|y_{2i}, y_{1i}, S_i, X_i, A_i\right)}{\partial s_{1i}}, \end{aligned} \tag{A7}$$

where $P(\cdot)$ denotes the probability of an event.

The right-hand side of the above expression for $s_{ji}, j = 1, 2, 3$, can be evaluated as follows:

$$\begin{aligned}\frac{\partial P\left(y_{3i}=1|y_{2i},y_{1i},S_i,X_i,A_i\right)}{\partial s_{ji}} =& \frac{\partial P\left(y_{3i}=1,y_{2i}=1,y_{1i}=1|y_{2i},y_{1i},S_i,X_i,A_i\right)}{\partial s_{ji}} \\ &+\frac{\partial P\left(y_{3i}=1,y_{2i}=0,y_{1i}=1|y_{2i},y_{1i},S_i,X_i,A_i\right)}{\partial s_{ji}} \\ &+\frac{\partial P\left(y_{3i}=1,y_{2i}=1,y_{1i}=0|y_{2i},y_{1i},S_i,X_i,A_i\right)}{\partial s_{ji}} \\ &+\frac{\partial P\left(y_{3i}=1,y_{2i}=0,y_{1i}=0|y_{2i},y_{1i},S_i,X_i,A_i\right)}{\partial s_{ji}}.\end{aligned}$$

We next evaluate the right-hand side of the above expression terms by terms:

$$\begin{aligned}&\frac{\partial P\left(y_{3i}=1,y_{2i}=1,y_{1i}=1|y_{2i},y_{1i},S_i,X_i,A_i\right)}{\partial s_{ji}} \\ =&\frac{\partial[\Phi(\delta+S_i\theta_3+X_{3i}\beta_3,\gamma+S_i\theta_2+\alpha A_i+A_i\times S_i\lambda+X_{2i}\beta_2,S_i\theta_1+X_{1i}\beta_1,\Omega)]}{\partial s_{ji}}.\end{aligned}$$

$$\begin{aligned}&\frac{\partial P\left(y_{3i}=1,y_{2i}=0,y_{1i}=1|y_{2i},y_{1i},S_i,X_i,A_i\right)}{\partial s_{ji}} \\ =&\frac{\partial[\Phi(S_i\theta_3+X_{3i}\beta_3,-(\gamma+S_i\theta_2+\alpha A_i+A_i\times S_i\lambda+X_{2i}\beta_2),S_i\theta_1+X_{1i}\beta_1,\Omega)]}{\partial s_{ji}}.\end{aligned}$$

$$\begin{aligned}&\frac{\partial P\left(y_{3i}=1,y_{2i}=1,y_{1i}=0|y_{2i},y_{1i},S_i,X_i,A_i\right)}{\partial s_{ji}} \\ =&\frac{\partial[\Phi(\delta+S_i\theta_3+X_{3i}\beta_3,S_i\theta_2+\alpha A_i+A_i\times S_i\lambda+X_{2i}\beta_2,-(S_i\theta_1+X_{1i}\beta_1),\Omega)]}{\partial s_{ji}}.\end{aligned}$$

$$\begin{aligned}&\frac{\partial P\left(y_{3i}=1,y_{2i}=0,y_{1i}=0|y_{2i},y_{1i},S_i,X_i,A_i\right)}{\partial s_{ji}} \\ =&\frac{\partial[\Phi(S_i\theta_3+X_{3i}\beta_3,-(S_i\theta_2+\alpha A_i+A_i\times S_i\lambda+X_{2i}\beta_2),-(S_i\theta_1+X_{1i}\beta_1),\Omega)]}{\partial s_{ji}}.\end{aligned}$$

The multivariate standard normal cumulative distribution function (cdf) is evaluated using a numerical approach proposed by Genz (1992) and implemented by the command *omxMnor* in the open-access *R* program *OpenMx* (Boker et al., 2011). In computing the total, direct and indirect marginal effects, for binary explanatory variables, the derivative is calculated as finite difference, e.g. as follows:

$$\Phi(.)|_{s_{ji}=1} - \Phi(.)|_{s_{ji}=0}.$$

For continuous explanatory variables, the derivative is numerically approximated by Richardson's extrapolation (see e.g. Linfield and Penny, 1989; Fornberg and Sloan, 1994) implemented by the command *grad* in the open-access *R* program *numDeriv*.

If the errors are uncorrelated across equations (as in the case of NSTEMI patients), Ω in the above expressions reduces to an identity matrix and the computation is simplified without having to resort to Genz (1992) approach.

The direct effect is the first item in RHS of (A7). Once the direct effect is obtained, given that the total effect is the sum of the direct and indirect effects, we then obtain the indirect effect as the difference between the total effect and direct effect. This applies to both correlated and uncorrelated errors.

Appendix B List of Coefficient Estimates

This Appendix contains the full listing of all coefficient estimates from estimating the base model of three probit equations discussed in the text. The estimation was carried out using the Stata command *Conditional (recursive) mixed-process (cmp)* (Roodman, 2011). Table B1 contains coefficient estimates obtained for STEMI patients, while Table B2 lists the estimates for NSTEMI patients.

Table B1: System Probit estimation: List of coefficient estimates, STEMI patients

	Dependent variable		
	Admission to cath-capable hosp.	Receive ICA	Survive 30 days post discharge
	Coeff	Coeff	Coeff
Admission to cath-capable hospital	–	4.247***	–
		(0.498)	
Receive ICA	–	–	0.326
			(0.279)
SEIFA (Ref: 1st quintile)			
2nd quintile	0.098	0.635*	0.006
	(0.202)	(0.290)	(0.067)
3rd quintile	0.101	0.527*	0.014
	(0.256)	(0.268)	(0.064)
4th quintile	0.209	0.841**	0.037
	(0.282)	(0.309)	(0.069)
5th quintile	0.202	0.884**	-0.017
	(0.247)	(0.297)	(0.076)
Private patient status	0.554***	0.380**	0.314***
	(0.168)	(0.144)	(0.058)
Remoteness (Ref: Metro)			
Inner Regional	-0.933***	–	-0.054
	(0.278)		(0.071)
Outer Regional	-1.383***	–	-0.084
	(0.269)		(0.092)
Male	0.072	0.217***	0.126***
	(0.045)	(0.041)	(0.037)
Age group (Ref: 44 or below)			
Age 45-49	-0.210*	-0.036	0.001
	(0.092)	(0.105)	(0.109)
Age 50-54	-0.059	-0.006	0.068
	(0.126)	(0.097)	(0.112)
Age 55-59	-0.060	-0.040	-0.007
	(0.129)	(0.096)	(0.108)
Age 60-64	-0.194†	-0.260**	-0.281*
	(0.108)	(0.093)	(0.120)
Age 65-69	-0.150	-0.302***	-0.416***
	(0.136)	(0.089)	(0.095)
Age 70-74	-0.450***	-0.331**	-0.536***
	(0.138)	(0.108)	(0.107)
Age 75-79	-0.600***	-0.688***	-0.714***
	(0.117)	(0.109)	(0.129)
Age above 80	-1.059***	-1.369***	-0.887***
	(0.136)	(0.135)	(0.156)

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	Dependent variable		
	Admission to cath-capable hosp.	Receive ICA	Survive 30 days post discharge
	Exp(Coeff)	Exp(Coeff)	Exp(Coeff)
Charlson comorbidity (Ref: Charlson < 2)			
Charlson $= 2$	-0.068	-0.535***	-0.427***
	(0.066)	(0.063)	(0.041)
Charlson $= 3$ or above	-0.185*	-0.988***	-0.713***
	(0.089)	(0.087)	(0.080)
Married	0.143***	0.147***	0.086*
	(0.044)	(0.035)	(0.040)
Australian born	-0.198*	-0.155***	0.014
	(0.080)	(0.043)	(0.030)
Arrival by ambulance	0.225†	-0.166*	-0.338***
	(0.126)	(0.067)	(0.039)
Financial year (Ref: 2011/12)			
Year 2005/06	0.052	0.164**	-0.031
	(0.082)	(0.059)	(0.052)
Year 2006/07	0.095	0.298***	-0.006
	(0.060)	(0.071)	(0.069)
Year 2007/08	0.237***	0.295***	-0.030
	(0.074)	(0.093)	(0.058)
Year 2008/09	0.145	0.370**	-0.067
	(0.130)	(0.120)	(0.066)
Year 2009/10	0.330**	0.447***	-0.071
	(0.119)	(0.099)	(0.066)
Year 2010/11	0.384***	0.552***	-0.081
	(0.090)	(0.096)	(0.062)
Admitted to teaching hospital	–	0.361**	0.006
		(0.120)	(0.056)
Admitted during weekend	0.003	-0.085	–
	(0.037)	(0.053)	
Month of admission (Ref: Jan)			
Feb	0.066	-0.044	-0.028
	(0.098)	(0.071)	(0.079)
Mar	-0.033	-0.030	0.009
	(0.095)	(0.072)	(0.079)
Apr	0.007	-0.122	-0.143
	(0.087)	(0.076)	(0.101)
May	0.053	-0.134†	-0.128
	(0.090)	(0.077)	(0.091)
Jun	0.021	-0.172**	-0.111†
	(0.094)	(0.054)	(0.061)
Jul	-0.149	-0.263***	-0.080
	(0.091)	(0.063)	(0.085)
Aug	-0.079	-0.176*	-0.106
	(0.090)	(0.079)	(0.080)
Sep	-0.018	-0.210**	0.022
	(0.077)	(0.066)	(0.080)
Oct	-0.087	-0.177*	-0.049
	(0.074)	(0.079)	(0.075)
Nov	-0.075	-0.160*	-0.006
	(0.068)	(0.078)	(0.078)
Dec	0.031	-0.175†	0.008
	(0.099)	(0.102)	(0.070)
Relative local prevalence of AMI	-0.257**	-0.011	–
	(0.082)	(0.057)	
No. of public hospital within 10km	0.054*	–	-0.002
	(0.025)		(0.005)
Capacity (Ref: very low)			
Low	–	0.622**	–
		(0.203)	
Medium	–	0.623†	–
		(0.328)	

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	Dependent variable		
	Admission to cath-capable hosp.	Receive ICA	Survive 30 days post discharge
	Exp(Coeff)	Exp(Coeff)	Exp(Coeff)
High	–	0.729*	–
		(0.351)	
Capacity× SEIFA			
Low× 2nd quintile	–	-0.607**	–
		(0.198)	
Low× 3rd quintile	–	-0.552**	–
		(0.201)	
Low× 4th quintile	–	-0.688***	–
		(0.209)	
Low× 5th quintile	–	-0.608**	–
		(0.222)	
Med× 2nd quintile	–	-0.513	–
		(0.317)	
Med× 3rd quintile	–	-0.438	–
		(0.281)	
Med× 4th quintile	–	-0.630*	–
		(0.317)	
Med× 5th quintile	–	-0.760*	–
		(0.326)	
High× 2nd quintile	–	-0.571†	–
		(0.311)	
High× 3rd quintile	–	-0.544†	–
		(0.320)	
High× 4th quintile	–	-0.795*	–
		(0.350)	
High× 5th quintile	–	-0.811*	–
		(0.336)	
Capacity× Priv patient			
Low× Private	–	-0.083	–
		(0.137)	
Med× Private	–	0.031	–
		(0.160)	
High× Private	–	0.142	–
		(0.136)	
Constant	1.742***	-3.760***	1.674***
	(0.320)	(0.596)	(0.222)
ρ_{12}	-0.287		
	(0.250)		
ρ_{13}	0.061		
	(0.087)		
ρ_{23}	0.312*		
	(0.139)		
N		13,468	

Note: (1) System of equations estimated using Stata command *cmp*.
(2) Robust standard errors shown in parentheses are obtained via clustering by hospital.
(3) Estimates for ρ_{ij} are not exponentiated.
(4) Significance levels: †: 10% *: 5% **: 1% ***: 0.1%

Table B2: System Probit estimation: List of coefficient estimates, NSTEMI patients

	Dependent variable		
	Admission to cath-capable hosp.	Receive ICA	Survive 30 days post discharge
	Coeff	Coeff	Coeff
Admission to cath-capable hospital	–	3.023***	–
		(0.239)	
Receive ICA	–	–	0.745***
			(0.037)
SEIFA (Ref: 1st quintile)			
2nd quintile	-0.115	0.408	-0.042
	(0.227)	(0.262)	(0.049)
3rd quintile	-0.016	0.393†	0.043
	(0.277)	(0.223)	(0.048)
4th quintile	-0.275	0.625*	-0.045
	(0.352)	(0.262)	(0.055)
5th quintile	-0.280	0.625*	-0.054
	(0.309)	(0.260)	(0.061)
Private patient status	0.432**	0.470***	0.029
	(0.153)	(0.117)	(0.021)
Remoteness (Ref: Metro)			
Inner Regional	-0.905**	–	0.017
	(0.337)		(0.036)
Outer Regional	-1.328***	–	0.036
	(0.289)		(0.047)
Male	0.119***	0.153***	-0.050**
	(0.024)	(0.021)	(0.017)
Age group (Ref: 44 or below)			
Age 45-49	-0.016	-0.011	-0.227
	(0.085)	(0.067)	(0.194)
Age 50-54	-0.054	-0.019	-0.238
	(0.085)	(0.082)	(0.147)
Age 55-59	-0.024	-0.107	-0.378*
	(0.092)	(0.072)	(0.153)
Age 60-64	-0.055	-0.279***	-0.588***
	(0.092)	(0.080)	(0.171)
Age 65-69	-0.185†	-0.381***	-0.566***
	(0.099)	(0.078)	(0.148)
Age 70-74	-0.324***	-0.534***	-0.639***
	(0.096)	(0.080)	(0.172)
Age 75-79	-0.519***	-0.829***	-0.810***
	(0.096)	(0.085)	(0.151)
Age above 80	-0.823***	-1.570***	-0.946***
	(0.107)	(0.075)	(0.161)
Charlson comorbidity (Ref: Charlson < 2)			
Charlson $= 2$	-0.003	-0.615***	-0.433***
	(0.041)	(0.030)	(0.022)
Charlson $= 3$ or above	-0.016	-0.951***	-0.733***
	(0.059)	(0.036)	(0.039)
Married	0.083**	0.174***	0.059**
	(0.028)	(0.017)	(0.023)
Australian born	-0.157*	-0.047	-0.037
	(0.063)	(0.035)	(0.026)
Arrival by ambulance	0.146	-0.443***	-0.182***
	(0.123)	(0.058)	(0.024)
Financial year (Ref: 2011/12)			
Year 2005/06	-0.026	0.069	-0.027
	(0.084)	(0.044)	(0.048)
Year 2006/07	0.018	0.071	-0.020
	(0.057)	(0.055)	(0.043)
Year 2007/08	0.017	0.083	0.015
	(0.070)	(0.053)	(0.052)
Year 2008/09	-0.103	0.102†	0.020

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	Dependent variable		
	Admission to cath-capable hosp.	Receive ICA	Survive 30 days post discharge
	Coeff	Coeff	Coeff
	(0.160)	(0.062)	(0.045)
Year 2009/10	0.063	0.146**	0.026
	(0.107)	(0.049)	(0.046)
Year 2010/11	0.146†	0.098†	-0.051
	(0.079)	(0.052)	(0.062)
Admitted to teaching hospital	–	0.142†	-0.001
		(0.073)	(0.036)
Admitted during weekend	0.010	-0.073*	–
	(0.026)	(0.032)	
Month of admission (Ref: Jan)			
Feb	0.082*	0.070*	0.090**
	(0.039)	(0.034)	(0.035)
Mar	0.020	0.006	0.035
	(0.047)	(0.053)	(0.034)
Apr	-0.069	0.008	0.048
	(0.046)	(0.037)	(0.040)
May	-0.033	0.016	0.017
	(0.050)	(0.046)	(0.040)
Jun	-0.086†	0.010	0.012
	(0.044)	(0.036)	(0.037)
Jul	-0.049	-0.068*	0.039
	(0.042)	(0.034)	(0.032)
Aug	-0.037	-0.076	0.040
	(0.049)	(0.048)	(0.041)
Sep	-0.044	-0.049	0.034
	(0.046)	(0.046)	(0.040)
Oct	-0.092†	0.041	0.046
	(0.047)	(0.040)	(0.040)
Nov	-0.029	0.017	0.047
	(0.041)	(0.043)	(0.048)
Dec	-0.007	-0.067	0.140***
	(0.040)	(0.052)	(0.043)
Relative local prevalence of AMI	-0.036	-0.030	–
	(0.052)	(0.036)	
No. of public hospital within 10km	0.074*	–	0.009**
	(0.030)		(0.003)
Capacity (Ref: very low)			
Low	–	0.434*	–
		(0.173)	
Medium	–	0.515†	–
		(0.288)	
High	–	0.485	–
		(0.315)	
Capacity× SEIFA			
Low× 2nd quintile	–	-0.304	–
		(0.190)	
Low× 3rd quintile	–	-0.285*	–
		(0.139)	
Low× 4th quintile	–	-0.406*	–
		(0.178)	
Low× 5th quintile	–	-0.361*	–
		(0.178)	
Med× 2nd quintile	–	-0.318	–
		(0.264)	
Med× 3rd quintile	–	-0.316	–
		(0.224)	
Med× 4th quintile	–	-0.521*	–
		(0.256)	
Med× 5th quintile	–	-0.467†	–
		(0.261)	

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	Dependent variable		
	Admission to cath-capable hosp.	Receive ICA	Survive 30 days post discharge
	Coeff	Coeff	Coeff
High× 2nd quintile	–	-0.213	–
		(0.279)	
High× 3rd quintile	–	-0.388	–
		(0.239)	
High× 4th quintile	–	-0.542†	–
		(0.284)	
High× 5th quintile	–	-0.536†	–
		(0.286)	
Capacity× Priv patient			
Low× Private	–	-0.143*	–
		(0.068)	
Med× Private	–	-0.132	–
		(0.092)	
High× Private	–	-0.009	–
		(0.119)	
Constant	1.501***	-2.752***	2.185***
	(0.326)	(0.316)	(0.191)
N		42,167	

Note: (1) System of equations estimated using Stata command *cmp*.
(2) Robust standard errors shown in parentheses are obtained via clustering by hospital.
(3) Significance levels: †: 10% *: 5% **: 1% ***: 0.1%

Appendix C Robustness Results

This Appendix contains results from our robustness checks described in Section 5 in the main text. Table C1 and C2 report estimates of total, and direct and indirect effects of SES variables obtained from the model with the least number of exclusion restrictions, i.e., the just-identified probit model. Corresponding estimates from the linear probability model are shown in Tables C3 and C4.

Model with least number of exclusion restrictions

Table C1: Total effects of SES, just-identified probit model

	Admit to cath-capable hospital		Receive ICA		30-day Survival	
	y_1	p-val	y_2	p-val	y_3	p-val
STEMI						
Remoteness (v major cities)						
Inner regional	-0.136**	0.015	-0.107**	0.015	-0.030	0.126
(s.e.)	(0.055)		(0.044)		(0.019)	
Outer regional	-0.253***	<0.001	-0.212***	<0.001	-0.052*	0.033
(s.e.)	(0.074)		(0.060)		(0.024)	
SEIFA quintile (v 1st)						
2nd quintile	0.013	0.635	0.042†	0.075	0.006	0.762
(s.e.)	(0.027)		(0.024)		(0.021)	
3rd quintile	0.013	0.695	0.031	0.258	0.008	0.712
(s.e.)	(0.034)		(0.027)		(0.021)	
4th quintile	0.026	0.452	0.069*	0.047	0.020	0.323
(s.e.)	(0.035)		(0.035)		(0.020)	
5th quintile	0.026	0.411	0.067*	0.028	0.000	0.990
(s.e.)	(0.031)		(0.030)		(0.024)	
Private patient (v public)	0.063**	0.006	0.117***	<0.001	0.119***	<0.001
(s.e.)	(0.023)		(0.023)		(0.015)	
NSTEMI						
Remoteness (v major cities)						
Inner regional	-0.219*	0.025	-0.088*	0.028	-0.019	0.216
(s.e.)	(0.098)		(0.040)		(0.016)	
Outer regional	-0.362***	<0.001	-0.154***	<0.001	-0.031	0.136
(s.e.)	(0.094)		(0.041)		(0.021)	
SEIFA quintile (v 1st)						
2nd quintile	-0.021	0.613	0.040	0.137	-0.003	0.887
(s.e.)	(0.041)		(0.027)		(0.018)	
3rd quintile	-0.003	0.954	0.035	0.253	0.022	0.204
(s.e.)	(0.048)		(0.030)		(0.017)	
4th quintile	-0.052	0.451	0.039	0.336	-0.004	0.838
(s.e.)	(0.069)		(0.041)		(0.019)	
5th quintile	-0.053	0.378	0.047	0.234	-0.005	0.826
(s.e.)	(0.060)		(0.040)		(0.021)	
Private patient (v public)	0.079*	0.015	0.132***	<0.001	0.044***	<0.001
(s.e.)	(0.032)		(0.028)		(0.008)	

Notes: Standard errors obtained via delta method.
Significance levels: †: 10% *: 5% **: 1% ***: 0.1%

Table C2: Direct and indirect effects of SES, just-identified probit model

	Receive ICA (y_2)				Survival (y_3)			
	Indirect (fr y_1)		Direct		Indirect (fr y_1 & y_2)		Direct	
	M.E.	p-val	M.E.	p-val	M.E.	p-val	M.E.	p-val
STEMI								
Remoteness (v major cities)								
Inner regional	-0.107*	0.015	–		-0.011	0.387	-0.019	0.422
(s.e.)	(0.044)				(0.013)		(0.023)	
Outer regional	-0.212***	<0.001	–		-0.022	0.360	-0.029	0.322
(s.e.)	(0.060)				(0.025)		(0.030)	
SEIFA quintile (v 1st)								
2nd quintile	0.009	0.624	0.034†	0.100	0.004	0.432	0.002	0.922
(s.e.)	(0.018)		(0.020)		(0.005)		(0.022)	
3rd quintile	0.009	0.688	0.022	0.216	0.003	0.490	0.005	0.829
(s.e.)	(0.023)		(0.018)		(0.004)		(0.021)	
4th quintile	0.019	0.430	0.050*	0.028	0.007	0.406	0.013	0.570
(s.e.)	(0.024)		(0.023)		(0.008)		(0.023)	
5th quintile	0.019	0.372	0.048*	0.022	0.006	0.399	-0.006	0.800
(s.e.)	(0.021)		(0.021)		(0.007)		(0.025)	
Private (v public) patient	0.047**	0.008	0.070***	< 0.001	0.012	0.326	0.107**	< 0.001
(s.e.)	(0.018)		(0.015)		(0.012)		(0.019)	
NSTEMI								
Remoteness (v major cities)								
Inner regional	-0.088*	0.028	–		-0.024*	0.032	0.004	0.684
(s.e.)	(0.040)				(0.011)		(0.011)	
Outer regional	-0.154***	<0.001	–		-0.042***	<0.001	0.010	0.472
(s.e.)	(0.041)				(0.011)		(0.014)	
SEIFA quintile (v 1st)								
2nd quintile	-0.010	0.628	0.050*	0.025	0.010	0.155	-0.013	0.373
(s.e.)	(0.020)		(0.022)		(0.007)		(0.014)	
3rd quintile	-0.001	0.955	0.036†	0.077	0.009	0.275	0.013	0.386
(s.e.)	(0.023)		(0.020)		(0.008)		(0.015)	
4th quintile	-0.025	0.470	0.064**	0.003	0.010	0.366	-0.014	0.392
(s.e.)	(0.035)		(0.021)		(0.011)		(0.016)	
5th quintile	-0.028	0.410	0.075***	< 0.001	0.012	0.272	-0.017	0.356
(s.e.)	(0.034)		(0.021)		(0.011)		(0.018)	
Private (v public) patient	0.034*	0.018	0.097***	< 0.001	0.035***	< 0.001	0.009	0.187
(s.e.)	(0.015)		(0.020)		(0.007)		(0.007)	

Notes: Standard errors obtained via delta method.
Significance levels: †: 10% *: 5% **: 1% ***: 0.1%

Linear Probability Model

Table C3: Total effects of SES, linear probability model

	Admit to cath-capable hospital		Receive ICA		30-day Survival	
	y_1	p-val	y_2	p-val	y_3	p-val
STEMI						
Remoteness (v major cities)						
Inner regional	-0.196**	0.003	-0.155**	0.003	-0.026*	0.029
(s.e.)	(0.066)		(0.053)		(0.012)	
Outer regional	-0.339***	<0.001	-0.269***	<0.001	-0.038*	0.017
(s.e.)	(0.083)		(0.076)		(0.016)	
SEIFA quintile (v 1st)						
2nd quintile	0.015	0.705	0.116*	0.029	-0.012	0.404
(s.e.)	(0.040)		(0.053)		(0.014)	
3rd quintile	0.022	0.637	0.108†	0.062	-0.008	0.557
(s.e.)	(0.047)		(0.058)		(0.014)	
4th quintile	0.041	0.297	0.148*	0.023	-0.007	0.571
(s.e.)	(0.039)		(0.065)		(0.013)	
5th quintile	0.029	0.397	0.155*	0.025	-0.024	0.168
(s.e.)	(0.034)		(0.069)		(0.017)	
Private patient (v public)	0.064*	0.026	0.129***	<0.001	0.054***	<0.001
(s.e.)	(0.029)		(0.031)		(0.008)	
NSTEMI						
Remoteness (v major cities)						
Inner regional	-0.274**	0.008	-0.094*	0.014	-0.004	0.522
(s.e.)	(0.103)		(0.038)		(0.006)	
Outer regional	-0.429***	<0.001	-0.148***	<0.001	-0.002	0.814
(s.e.)	(0.088)		(0.039)		(0.010)	
SEIFA quintile (v 1st)						
2nd quintile	-0.028	0.614	0.050	0.198	-0.003	0.662
(s.e.)	(0.055)		(0.039)		(0.008)	
3rd quintile	0.003	0.960	0.052	0.149	0.008	0.266
(s.e.)	(0.064)		(0.036)		(0.007)	
4th quintile	-0.044	0.567	0.082†	0.071	-0.003	0.688
(s.e.)	(0.077)		(0.045)		(0.008)	
5th quintile	-0.038	0.526	0.093*	0.044	-0.003	0.775
(s.e.)	(0.060)		(0.046)		(0.009)	
Private patient (v public)	0.082*	0.025	0.138***	<0.001	0.012***	<0.001
(s.e.)	(0.036)		(0.023)		(0.003)	

Notes: Standard errors obtained via delta method.
Significance levels: †: 10% *: 5% **: 1% ***: 0.1%

Table C4: Direct and indirect effects of SES, linear probability model

	Receive ICA (y_2)				Survival (y_3)			
	Indirect (fr y_1)		Direct		Indirect (fr y_1 & y_2)		Direct	
	M.E.	p-val	M.E.	p-val	M.E.	p-val	M.E.	p-val
STEMI								
Remoteness (v major cities)								
Inner regional	-0.155**	0.003	–		0.031	0.404	-0.057	0.185
(s.e.)	(0.053)				(0.037)		(0.043)	
Outer regional	-0.269***	<0.001	–		0.054	0.378	-0.092	0.184
(s.e.)	(0.076)				(0.061)		(0.069)	
SEIFA quintile (v 1st)								
2nd quintile	0.012	0.705	0.104†	0.051	-0.023	0.293	0.011	0.553
(s.e.)	(0.032)		(0.054)		(0.022)		(0.019)	
3rd quintile	0.018	0.637	0.091†	0.073	-0.022	0.321	0.013	0.459
(s.e.)	(0.037)		(0.051)		(0.022)		(0.018)	
4th quintile	0.033	0.287	0.116†	0.052	-0.030	0.258	0.023	0.285
(s.e.)	(0.031)		(0.060)		(0.026)		(0.021)	
5th quintile	0.023	0.391	0.132*	0.046	-0.031	0.250	0.007	0.725
(s.e.)	(0.027)		(0.066)		(0.027)		(0.020)	
Private (v public) patient	0.051*	0.036	0.079***	< 0.001	-0.026	0.343	0.080**	0.003
(s.e.)	(0.024)		(0.021)		(0.027)		(0.027)	
NSTEMI								
Remoteness (v major cities)								
Inner regional	-0.094*	0.014	–		-0.007*	0.016	0.003	0.544
(s.e.)	(0.038)				(0.003)		(0.005)	
Outer regional	-0.148***	<0.001	–		-0.011***	<0.001	0.009	0.279
(s.e.)	(0.039)				(0.003)		(0.008)	
SEIFA quintile (v 1st)								
2nd quintile	-0.010	0.614	0.059	0.143	0.004	0.204	-0.007	0.334
(s.e.)	(0.019)		(0.040)		(0.003)		(0.007)	
3rd quintile	0.001	0.960	0.051	0.172	0.004	0.151	0.004	0.576
(s.e.)	(0.022)		(0.037)		(0.003)		(0.007)	
4th quintile	-0.015	0.567	0.097*	0.023	0.006†	0.080	-0.009	0.267
(s.e.)	(0.027)		(0.043)		(0.003)		(0.008)	
5th quintile	-0.013	0.528	0.106*	0.017	0.007*	0.049	-0.009	0.284
(s.e.)	(0.021)		(0.045)		(0.003)		(0.009)	
Private (v public) patient	0.028*	0.030	0.110***	< 0.001	0.010***	< 0.001	0.001	0.639
(s.e.)	(0.013)		(0.017)		(0.002)		(0.003)	

Notes: Standard errors obtained via delta method.
Significance levels: †: 10% *: 5% **: 1% ***: 0.1%


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