Competing Complements in Public-Private Hospital Markets

Kai Shen Lim*

kaishenlim@g.harvard.edu

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Abstract

Public hospitals in many developing countries provide subsidized care that competes with private hospitals while training specialists who later join the private sector. I study this tension between competition and complementarities using the staggered construction of public hospitals in Malaysia from 1996 to 2013. Specialist public hospitals increase private entry by 30 percent, while non-specialist hospitals show the opposite pattern. This heterogeneity reflects specialist physician labor market spillovers as specialist hospitals expand the local supply of trained specialists who later transition to private practice. A dynamic entry model estimates specialist hospitals reduce private entry costs by approximately 26 percent through this channel. Whether public hospitals crowd out or crowd in private hospitals thus depends on the balance between competition and complementarities.

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1 Introduction

Public provision crowds out private investment when public options reduce the demand for private alternatives. Public health insurance reduces private coverage (Cutler and Gruber, 1996; Gruber and Simon, 2008), public schools affect private enrollment (Dinerstein and Smith, 2021), and municipal broadband reduces private investment (Wilson, 2025). But public institutions may also generate complementarities for private firms through workforce training, knowledge spillovers, or the production of shared inputs. This tension between competition and complementarities is especially consequential for healthcare in developing countries, where private hospitals deliver a large and growing share of healthcare services (WHO, 2020). If public investment crowds out private supply, governments displace existing capacity rather than expand it. If it crowds in, each public hospital generates additional private capacity beyond its own direct provision.

Specialist physicians are important inputs for private hospitals. Unlike other medical professionals, specialists deliver clinical services such as surgery, obstetrics, and cardiology that require years of postgraduate residency training. In most developing countries, this training takes place exclusively in public teaching hospitals. Graduates typically serve in the public sector under compulsory service bonds before entering private practice. A new public hospital therefore reduces demand for nearby private hospitals while expanding the local supply of the specialized labor those hospitals require for entry. Whether the training spillover exceeds the competitive displacement of private demand determines the net effect on private entry, but separating the two channels empirically is difficult as both operate simultaneously whenever a new public hospital opens.

Malaysia's public hospital system provides an opportunity to make this separation. The healthcare system includes specialist hospitals, which house residency training programs and offer specialist clinical services, and non-specialist hospitals, which provide primary and secondary care without specialist training programs. Only specialist hospitals produce the trained specialist physicians who later enter private practice, and public hospitals hold a strict monopoly on clinical training for locally trained specialists[1]. Comparing private hospital responses to the construction of each type therefore provides variation in whether a new public facility generates training spillovers.

To identify the causal effects of public hospital construction on private entry, I exploit the staggered timing of public hospital openings across Malaysia between 1996 and 2013. I construct a new district-year panel linking administrative records on public hospital construction to private hospital entry counts from survey data and primary data collection. Public hospital placement is plausibly exogenous to private entry incentives as the two sectors respond to different factors. The Ministry of Health allocates public hospitals to underserved areas lacking existing facilities, while private hospitals target districts with population growth and ability to pay. The political origins of the construction program further reinforce this distinction. Following public backlash against proposed healthcare privatization in the mid-1990s, the government committed to building hospitals in constituencies that lacked public facilities, a criterion largely orthogonal to the profit considerations driving private entry.

Specialist public hospitals increase private entry by 30 percent relative to the pre-treatment stock of private hospitals in treated districts. Non-specialist public hospitals, constructed in districts with essentially no pre-existing private hospitals, produce directionally negative effects consistent with crowd-out. The heterogeneity maps directly onto two mechanisms. Specialist hospitals generate specialist supply spillovers large enough to offset their competitive effect on demand, while non-specialist hospitals reduce demand without producing offsetting complementarities. Therefore, the same government investment crowds in or crowds out private entry depending on whether the public facility trains specialist physicians.

Individual-level data from Malaysia's physician registry provide direct evidence on the training channel. A cross-sectional snapshot of 12,503 registered specialists in 2025 shows that approximately 40 percent of specialists whose compulsory service bonds have expired

[1] While specialist degrees are conferred by both public and private universities, clinical residency training takes place in Ministry of Health hospitals regardless of the degree-granting institution.

currently practice in the private sector. The public sector trains all specialists through its monopoly on clinical residency, yet the private sector, which accounts for only 28 percent of total hospital beds, absorbs nearly half of the specialist supply. Among 252 specialists from recent cohorts observed transitioning from public to private practice within the registry window, 61 percent remain in the same district as their last public posting or within the greater Kuala Lumpur metropolitan area. The pipeline from public training to private practice is large and geographically concentrated.

Several additional mechanisms support the training interpretation. Census data show that the district-level stock of private specialists increases after specialist public hospital construction, with timing consistent with residency duration, even as specialist public hospitals simultaneously reduce private hospital admissions. Private-sector nurses and health technicians, who are also trained in public hospitals show no such spillover effects. Between 2003 and 2012, 35 existing specialist hospitals that expanded bed capacity without adding new training positions show no significant effect on private hospital entry.

Within treated districts, the spatial pattern of private entry is consistent with both competition and complementarities occurring simultaneously. Private entry declines in the immediate vicinity of the new public hospital where patient competition is most intense, rises at intermediate distances where the physician labor pool remains accessible but competition is attenuated, and falls again at greater distances where commuting costs limit physician access. This non-monotonic gradient provides within-district evidence that the crowd-in reflects an interaction between opposing effects rather than an artifact of cross-district heterogeneity.

The reduced-form evidence shows that specialist hospitals crowd in private entry while non-specialist hospitals crowd out. To quantify how specialist supply spillovers affect private entry incentives, I estimate a dynamic entry model where potential entrants choose districts based on expected profit streams (Bajari et al., 2007). Estimating profits requires demand and price data, which I combine from electronic health records on hospital admissions and primary collection of private hospital prices. The model recovers entry costs that rationalize observed private hospital location decisions. The estimates show that specialist public hospitals reduce private entry costs by 26 percent through expanded specialist supply.

When public and private providers are substitutes, public provision crowds out private investment as prior work demonstrates. When public facilities bundle service provision with input production that benefits private entrants, the net effect depends on whether input complementarities offset demand substitution. In public-private hospital markets, specialist training is the key complementary input. Public hospitals that train specialists reduce private entry costs sufficiently to exceed the competitive effect of subsidized care. Hospitals that do not train specialists crowd out private investment as in other sectors. This mechanism likely extends beyond Malaysia, as many developing countries concentrate specialist training in public teaching hospitals while private hospitals hire from the publicly-trained physician pool.

Related Literature. This paper contributes to the literature on public provision and private market responses across education (Epple and Romano, 1998; Hoxby, 2000; Dinerstein and Smith, 2021), health insurance (Cutler and Gruber, 1996; Duggan and Scott Morton, 2006; Saltzman, 2023), pharmacies (Atal et al., 2024), broadband (Wilson, 2025), and consumer goods (Jiménez Hernández and Seira, 2022). Recent work shows that crowd-in is possible under specific conditions. Competitive pressures from public school funding raise private school quality (Andrabi et al., 2024), and public research labs generate local R&D spillovers to private firms partly through researcher mobility (Bergeaud et al., 2025). This paper's contribution is identifying labor market spillovers from public training institutions as a distinct mechanism through which public provision crowds in private investment. While a large hospital competition literature exists for the United States (Gaynor et al., 2014; Ho and Lee, 2017; Shepard, 2022), few studies examine public-private hospital competition in developing countries, where patients pay out-of-pocket and public hospitals dominate specialist training (Das et al., 2008; Banerjee et al., 2024).

This paper also provides empirical evidence on mixed public-private competition, a literature that has been largely theoretical (Cremer et al., 1991; De Fraja and Valbonesi, 2009;

Klumpp and Su, 2019) with limited empirical work on hospitals (Bloom et al., 2015; Herr, 2011). I show that competitive outcomes in mixed markets depend on the specific characteristics of public providers, particularly whether they generate complementarities that benefit private competitors. The results also connect to the place-based policies literature (Kline and Moretti, 2014; Juhász et al., 2024), showing that public provision can stimulate private investment through workforce training in addition to targeted industrial policies.

The paper proceeds as follows. Section 2 provides context and data on the Malaysian public and private hospital industry. Section 3 presents descriptive facts about the public-private hospital market. Section 4 presents the reduced-form results. Section 5 estimates the structural model to recover entry costs. Section 6 concludes.

2 Context and Data

2.1 History of the Public-Private Malaysian Health System

Following Malaysia's independence from the British Empire in 1957, the Ministry of Health established a network of public hospitals to ensure universal access to healthcare services. This public system operated as the dominant healthcare provider until the 1980s, when Malaysia adopted a series of broader economic liberalization policies extended to the healthcare sector. The privatization wave of the early 1980s was a key policy shift in Malaysia's health system. The government actively encouraged private investment through tax breaks for medical devices and private health insurance (Barraclough, 2000). These nationwide policies allowed private investors to enter markets based on profit considerations rather than central planning directives.

However, by the mid-1990s, political resistance to healthcare privatization emerged as a constraint on further market oriented policies. The government's initial plans to corporatize public healthcare services faced significant opposition from the ruling coalition's constituents, who viewed potential reductions in subsidized public healthcare as a threat to equitable medical care.[2] This political backlash resulted in a policy reversal that reinforced the government's commitment to maintaining a robust public healthcare system alongside the growing private sector.

The 1995 general election became a pivotal moment that shaped Malaysia's public-private healthcare system. Rather than pursuing further privatization of public services, the government responded to electoral pressures by expanding public hospital capacity and reaffirming subsidized public healthcare as a core public good. As a result, Malaysia developed hospital markets where private hospitals operate as an expensive alternative to a heavily subsidized public system, rather than as replacements for public provision.[3]

Importantly for the event studies, the government's renewed commitment to public hospital expansion post-1995 provides an empirical opportunity to examine the effects of public hospitals on private investment. The construction of public hospitals following the electoral mandate creates variation in public hospital entry location and timing, which I use in the event study analyses to identify causal effects on private hospital entry.

2.2 Hospital Classification, Regulation, and Pricing

The Ministry of Health classifies public hospitals into four tiers based on specialization and capacity. State hospitals and major specialist hospitals (Level 4) offer the full range of specialty and subspecialty services. Minor specialist hospitals (Level 3) provide a more limited set of specialist services. Non-specialist hospitals (Levels 1–2) provide general medical and nursing care staffed by medical officers rather than specialists. In the event study analysis, I group state hospitals, major specialist hospitals, and minor specialist hospitals as "specialist" hospitals, since all three tiers operate residency training programs. Non-specialist hospitals do not train specialists.

[2]In 1985, Prime Minister Mahathir Mohamad announced a series of privatization and corporatization policies across multiple industries. This led to political concern from the main coalition's constituents, as the government contemplated reducing subsidized public healthcare services. In the 1995 Malaysia general elections, the government retracted all policies related to corporatizing public healthcare services and increased the number of public hospitals to show commitment to retaining a public-dominant health system Barraclough (1997, 2000).

[3]The 1997–98 Asian Financial Crisis caused Malaysia's GDP to contract by 7.4 percent in 1998. Public expenditure fell short of planned targets in 1998 and 1999, likely delaying some hospital construction projects planned under the Seventh Malaysia Plan (1996–2000). Because the crisis affected all of Malaysia simultaneously, these delays are absorbed by year fixed effects in the event study specification.

Public hospital allocation follows a multi-tiered process embedded within Malaysia's five-year development planning cycle. Hospital funding is allocated to districts based on the Malaysia Plans, which are national development blueprints that prioritize healthcare accessibility and population coverage. The Ministry of Health collaborates with State Economic Planning Units to identify districts requiring new healthcare infrastructure based on demographic projections, existing facility capacity, and accessibility gaps (see Figure A.7 for excerpts from official planning documents). After districts receive funding allocations through this centralized planning process, local health authorities work with district officials to identify specific sites that maximize population access while considering factors such as land availability, transportation networks, and proximity to existing health facilities.

In contrast, private hospital entry operates under a regulatory framework established by the Private Healthcare Facilities and Services Act 1998. While the Ministry of Health retains approval authority for private hospital licenses, the regulatory standard primarily requires demonstration of sufficient local demand rather than adherence to national planning objectives. Private hospitals can choose any location within a district based on commercial considerations such as population density, income levels, and competitive positioning. In short, private entrants seek to make profits, while public hospitals are centrally allocated based on accessibility objectives.

The regulatory framework governing pricing differs between sectors. Public hospitals operate under a unified national pricing structure, with the government setting standardized fees for all services across the country but varying by room types. These prices are heavily subsidized. For example, a normal delivery in a public hospital costs Malaysian citizens MYR 100 (approximately USD 24) in a third-class ward. Private hospitals face a more complex regulatory environment. While the 1998 Act establishes fee schedules for physician consultations and medical procedures, it does not regulate hospital-specific charges such as room fees, meals, and ancillary services. This partial price regulation allows private hospitals significant flexibility to price their services based on local market conditions and competition.

2.3 Physician Training and the Public-to-Private Pipeline

Malaysia requires all physicians to complete a four-year mandatory service obligation in public hospitals, comprising housemanship training and compulsory service as a medical officer, before practicing independently.[4] After completing this obligation, physicians choose between remaining in public sector employment, which offers civil service job security and fixed salaries, and entering private practice with fee-for-service compensation.

Specialist training imposes additional years of public service. All physicians seeking specialization must complete a Master of Medicine (MMed) residency program lasting four to six years depending on the discipline, conducted in Ministry of Health hospitals.[5] Trainees receive full sponsorship under the *Hadiah Latihan Persekutuan* (HLP) scholarship administered by the Public Service Department, which bonds them to public service for an additional four to seven years after completing specialization.[6] After a six-month gazettement process for formal recognition, specialists may resign from government service and enter private practice once their bond obligation is fulfilled.

This institutional arrangement means that specialist public hospitals serve as both healthcare providers and training centers for the entire healthcare labor market. The combined duration of residency and bond service implies that the earliest a new specialist hospital could produce physicians available for private employment is approximately five to eight years after the hospital begins training. Non-specialist hospitals, which do not operate residency programs, produce no such training spillovers.

During the study period (1996–2013), formal dual practice was not permitted. The Ministry of Health introduced a limited dual practice policy in 2007 that allowed public specialists to treat private patients within the same public hospital for additional fees,

[4] Prior to 2008, this obligation consisted of one year of housemanship and three years of compulsory service. In 2008, housemanship was extended to two years and compulsory service was reduced to two years, keeping the total at four years.

[5] While specialist degrees are conferred by both public and private universities, clinical residency training takes place in Ministry of Health hospitals regardless of the degree-granting institution. A small number of specialists obtain qualifications abroad and register through the National Specialist Register upon return.

[6] The bond penalty ranges from RM 500,000 to RM 700,000 depending on whether training is conducted locally or overseas. In practice, enforcement is limited: specialists who resign typically repay the penalty in small monthly installments, reducing the effective cost of early departure from public service.

but this arrangement does not extend to practicing at external private facilities (Fadzil et al., 2022). The primary channel through which publicly trained specialists enter the private sector is therefore full resignation from government service after completing bond obligations, rather than gradual moonlighting.

2.4 Data

I provide a brief overview of the data used in the event study analyses and structural model separately, and further details can be found in Appendix A. A summary of the key variables is tabulated in Table A.1. The event study data comes from a combination of administrative data and surveys conducted by the Ministry of Health. The structural model combines aggregated electronic health records with hospital maternity package prices that I collected in 2022, and micro moments from a national survey of families planning to have children.

Event Study Data. I estimate my events studies using a district-level panel data across all Malaysian districts over 1996-2013.[7] The analysis focuses on 25 new public hospitals that began operations between 1996 and 2013, and their impact on the stock of private hospitals across districts. By 2013, there were 269 hospitals total in the sample: 135 public and 134 private. I construct this panel using data from the National Healthcare Establishment and Workforce Survey (NHEWS), which contains information about every hospital providing hospitalization services that was operational in 2013. Using each hospital's construction and opening dates, I backfill the count of public and private hospitals operating in each district for every year from 1996 to 2013. The final dataset includes all general and specialized hospitals providing acute curative care from both public and private sectors. I exclude specialized institutions (prison, defense, and education ministry hospitals) and long-term care facilities (rehabilitative and palliative care hospitals, nursing homes, leprosy centers, and psychiatric institutions).

To understand the mechanisms driving private hospital entry patterns, I use two additional outcome data measured at the district level. Data on private specialist physicians

[7] The sample includes districts in both Peninsular Malaysia and East Malaysia (Sabah and Sarawak). Eight of the 25 treatment events occur in East Malaysia, where healthcare markets are more rural and private hospitals are less prevalent.

comes from the Population and Housing Census for 1970, 1980 and 1991[8]. I use district-level counts of self-employed physicians as a proxy for private specialist physicians, since all public specialist physicians are civil servants receiving wages rather than operating independently. This implies that my outcome is an undercount of total private specialists, but it captures the majority of private specialists who operate their own clinics or work in private hospitals.

Data on private hospital utilization comes from the National Health and Morbidity Survey conducted in 1996, 2006, and 2011. This nationally representative survey interviews approximately 59,000 respondents in 1996 and 2006, while 29,000 in 2011. The survey asks about healthcare utilization in the previous year, including private inpatient admissions. The survey weights allow for district-level estimation of private hospital utilization rates. Combining the survey data yields 396 district-year observations (132 districts $\times$ 3 years) for this analysis. These surveys are used by the Ministry of Health for planning purposes, providing confidence in their reliability and comparability across survey years.

Data on individual specialist physicians comes from Malaysia's Annual Practicing Certificate (APC) registry. I collect the complete registry of practicing specialists and cross-match it with the National Specialist Register (NSR) to identify specialist qualification years and fields of practice. The resulting dataset covers 12,463 registered specialists observed across 2023–2026, recording each physician's primary practice location, sector (public, private, or university), specialty, medical school, and year of specialist qualification. The qualification year ranges from 1950 to 2024, providing variation in how long each specialist has had to complete bond obligations and potentially transition to private practice. Because the APC is a mandatory annual license required for all practicing physicians, the data captures the near-universe of actively practicing specialists in Malaysia regardless of sector. I use this data to document the public-to-private transition rate by qualification cohort and

[8]Data on private specialist physicians comes from the Population and Housing Census for 1970, 1980 and 1991.The 2000 census adopted revised ISCO occupation codes that combine physicians, veterinarians, dentists, and other medical professionals into a single category, precluding identification of specialist physicians. I therefore cannot construct district-level physician counts during the study period itself using census data.

the geographic concentration of transitions, providing direct evidence on the physician training pipeline described in Section 2.3.

Finally, I use 'Health Facts', an annual publicly available dataset containing hospital-level information on total beds from 2003-2013, to construct an alternative treatment of hospital upgrades. Health Facts covers the same hospitals as NHEWS, allowing me to identify existing hospitals that received significant capacity upgrades (defined as increases in bed count). I observe 49 such upgrades across different hospitals during this period. This alternative treatment tests whether the private hospital entry effects are specific to entirely new public hospital construction, or also occur when existing public hospitals expand their capacity.

Structural Model Data. I use four data sources for demand estimation and the dynamic entry model. My data covers 95 districts (out of 133 possible districts, see Figure C.8) after dropping areas with missing survey coverage or hospital price data.

I obtain hospital admissions data from the Ministry of Health's electronic health records systems. Public hospital admissions come from the *Sistem Maklumat Rekod Pesakit* (SMRP), while private hospital admissions come from the Private Hospital Discharge Database (PHDD). Both systems record patient demographics, diagnosis codes, admission and discharge dates, and treating hospital for all admissions in 2013. I use ICD-10 diagnosis codes to identify patients admitted for normal vaginal deliveries, which serves as the main dataset for demand estimation. The 2013 timing requires backprojecting demand patterns for the dynamic entry model.

The family survey on birth delivery preferences and demographic characteristics comes from the National Health and Morbidity Survey (NHMS) 2015. The survey includes approximately 5,000 families with childbearing intentions across the 95 districts in my estimation sample. For respondents planning to have children, the survey records stated hospital choice for delivery alongside individual demographics including income, insurance status, and chronic disease history that are not available in the administrative admissions data. The survey also elicits perceptions of hospital quality and waiting times on Likert scales, which I use to characterize differences in patient experience across sectors. I geocode respondents' locations and match them to all available hospitals in their district, calculating straight-line distances to construct individual-to-hospital choice sets for the random coefficients logit demand estimation. These survey responses provide the micro moments for BLP estimation.

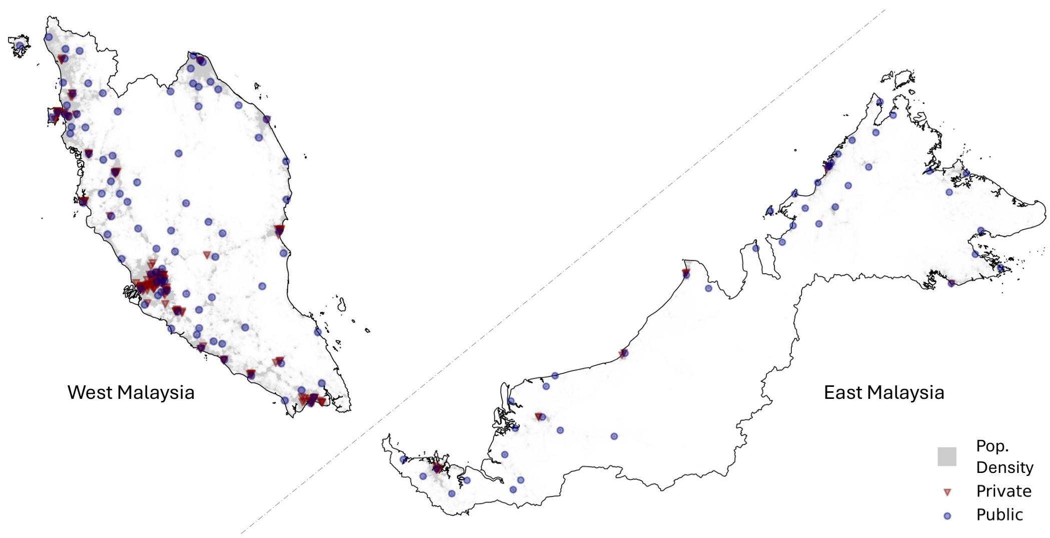
I conduct primary data collection in 2022 to compile hospital-specific prices for normal delivery packages. Private hospitals advertise flat-fee maternity packages through websites and social media, differentiated by room type and services (See Figure C.7 for examples of such posters). I collect the minimum advertised price for each private hospital through direct contact, website research, and social media monitoring. Private hospitals that did not respond (27 out of 134 private hospitals) are dropped from the demand estimation sample. Public hospitals charge a standardized subsidized rate of RM100 for normal delivery in third-class wards. I assume that relative price differences across hospitals remain stable when backprojected from 2022 collection to 2013 for demand estimation. This assumption could be problematic if there were systematic changes in pricing strategies during 2013-2021. However, the continued growth of private hospitals from 134 to 202[9] by 2021 with minimal exits suggests an increasingly competitive and profitable market, meaning 2021 prices may underestimate historical price levels. Land price data comes from the National Property Information Centre (NAPIC) for 2022, providing commercial land prices per square foot for each district. This data serves as a proxy for fixed sunk costs in the supply-side estimation.

3 Descriptive Evidence

Private hospitals concentrate in urban areas while public hospitals distribute more evenly across the country. Figure 1 maps hospital locations in 2013 against population density, showing this clustering pattern. Figure A.3 shows how this geographic pattern has changed over time. Between 1980 and 2013, private hospitals expanded primarily in urban centers while public hospitals grew in rural areas.

[9] Data from Health Facts 2021.

Figure 1: Public and Private Hospitals Location in 2013



Note: Hospital location data are from the National Healthcare Establishment Workforce Survey (2013). Population density are 1km grids from the Center for Integrated Earth System Information (CIESIN).

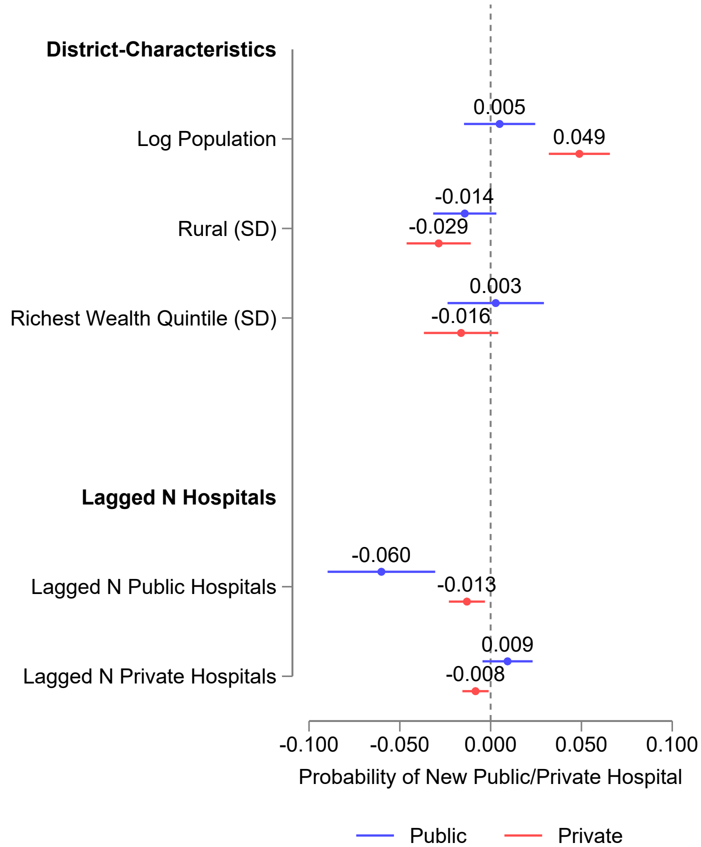
Despite their urban concentration, private hospitals operate at a significantly smaller scale than public specialist hospitals and capture limited market share (Table A.1). The 134 private hospitals in the event study sample average 94 beds, compared to 509 beds for public specialist hospitals and 89 beds for non-specialist public hospitals. The sector includes large corporate chains such as KPJ Healthcare (16 percent) and Pantai Holdings (8 percent), but 65 percent of private hospitals are independently owned specialist centers, typically founded by one or a small group of specialist physicians (Table A.1, Panel A). For most private hospitals in Malaysia, recruiting specialist physicians is a key binding constraint for establishment. The law requires every private hospital to appoint a medically qualified person in charge with specialty training, and small independent hospitals typically depend on their founding physician to fill this role.

For maternity services, private hospitals hold just 8 percent of district market share for vaginal deliveries, while public specialist and non-specialist hospitals capture 70–79 percent (Table A.1, Panel B). The remaining share reflects the outside option of home births, traditional birth attendants, and private maternity clinics. This small market share occurs despite public specialist hospitals facing congestion: public specialist hospitals exhibit 73.9 percent bed occupancy compared to 47.3 percent for public non-specialist hospitals and 53.9 percent for private hospitals (Table A.1, Panel A). The congestion creates wait time dissatisfaction among public hospital patients (3.23 vs 3.82 satisfaction rating for private hospitals), yet survey respondents still rate public hospitals higher on overall quality (4.03 vs 3.83 for private hospitals; Table A.1, Panel C).

The limited overlap between public and private hospitals partly reflects segmented price markets. Private maternity services cost 3,306 MYR compared to 100 MYR for subsidized public services (Table A.1, Panel B). This price gap corresponds to differences in the patient populations they serve. Private hospital users have higher monthly incomes (2.54 vs 1.52 thousand MYR), shorter travel distances to private facilities (15.31 vs 31.82 km), and higher private insurance rates (0.52 vs 0.16; Table A.1, Panel C).

These differences extend to location decisions. Figure 2 presents the average marginal effects of district characteristics on the probability of public and private hospital entry from a logit model with year fixed effects. I omit district fixed effects to compare the characteristics of districts that received a new hospital to those that did not within the same year. The results show that the covariates predicting private entry differ from those predicting public entry. Private hospitals enter districts with higher population and lower proportion of rural residents. Public hospitals, conversely, are significantly less likely to enter districts that already have a public hospital, consistent with the Ministry of Health's stated objective of expanding access to underserved areas rather than duplicating existing public capacity. Factors that strongly predict private entry, such as population and urbanization, show weaker or statistically insignificant associations with public hospital placement. While this descriptive evidence does not rule out all potential confounding, it suggests that public hospital allocations are not primarily driven by the same profit considerations that incentivize private hospital entry.

Figure 2: Descriptive Evidence on Public and Private Hospital Entry



Note: These are average marginal effects from logit regressions of public (or private) hospital entry on a set of district characteristics with year fixed effects. The data consists of public and private entry between 1996 and 2013. The mean probability for public entry is 0.016 while it is 0.024 for private hospitals. The full coefficient plot can be found in Figure A.5. The dependent variable is a binary variable for whether a district-year receives a new public (or private) hospital. Standard errors are clustered at the district level.

4 Reduced Form Evidence

4.1 Impact of New Public Hospitals on Private Entry

Identifying the impact of new public hospitals on private entry requires addressing the endogenous placement of public facilities. The Ministry of Health allocates public hospitals based on accessibility, population, and congestion at existing facilities which may also drive private entry. I exploit variation in the timing of public hospital construction across 25 treated districts and 22 never-treated controls in a staggered event study design (Figure B.1 maps these districts). Treatment and control districts are well-balanced on pre-treatment demographics, socioeconomic status, education, and existing health infrastructure, with modest differences in population and rurality absorbed by district fixed effects (Table B.1).

I estimate the interaction-weighted event study specification of Sun and Abraham (2021), which avoids the contamination bias that can arise in conventional two-way fixed effects (TWFE) estimation under staggered treatment timing (Sun and Abraham, 2021; de Chaisemartin and D'Haultfœuille, 2024). The estimator recovers cohort-specific average treatment effects on the treated using never-treated districts as the comparison group for each cohort separately. In practice, the SA and TWFE estimates are nearly identical (see Table B.7), suggesting that heterogeneity bias is negligible in this setting.

$$Y_{dt} = \delta_d + \lambda_t + \sum_{e \in \mathcal{E}} \sum_{\ell \neq -1} \delta_{e,\ell} \, \mathbf{1}\{E_d = e\} \, D^{\ell}_{dt} + \varepsilon_{dt} \tag{1}$$

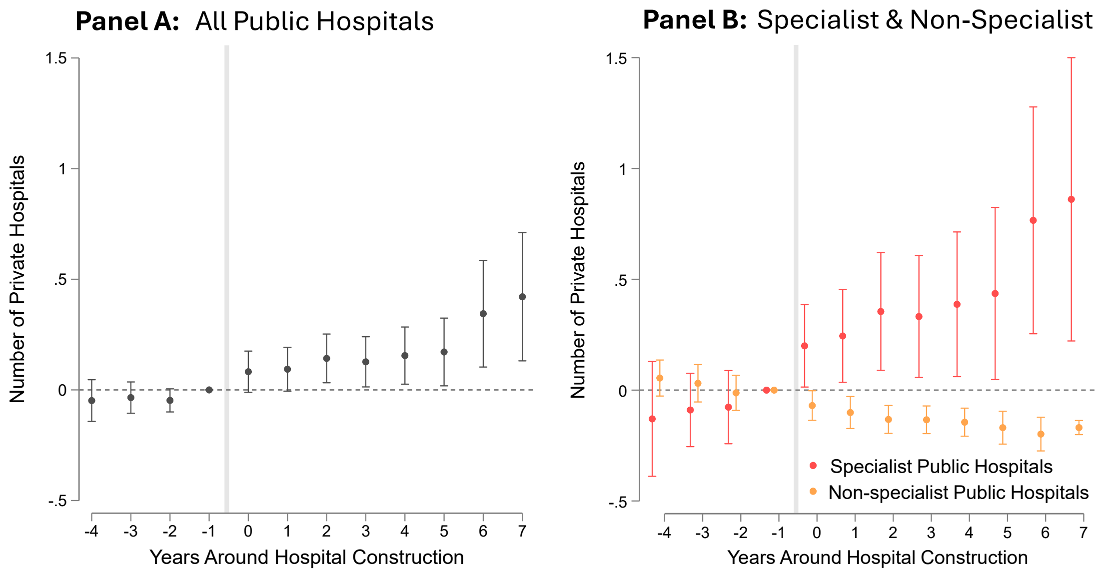
where Y_{dt} is the number of private hospitals in district d at time t, δ_d and λ_t are district and year fixed effects, E_d is the year district d receives its first public hospital, and $\ell = -1$ is the reference period.[10] I estimate three specifications: pooling all public hospitals, and separating specialist from non-specialist hospitals.

Figure 3 shows parallel pre-trends across all specifications, with coefficients close to zero in the four years before construction. The pooled effect masks substantial heterogeneity by hospital type (Panel B). Subsequent tables report two baseline measures. 'Mean Dep. Var.' is the mean outcome across all district-years in the estimation sample, pooling treated and control districts. 'Pre-Treatment Mean' isolates treated districts before treatment, and provides the relevant baseline for computing percentage effects. The two measures are both reported because while 'Pre-Treatment Mean' is the natural baseline for percentage effects, it is zero for non-specialist districts that had no private hospitals before treatment, making the pooled mean necessary as an alternative reference for the magnitude of those effects.

Specialist public hospitals generate crowd-in effects that appear immediately at the year of construction and grow steadily over the post-treatment window, increasing the stock of private hospitals in treated districts by about 30 percent on average and adding roughly

[10] I include relative time indicators for $\ell \in \{-10, \ldots, -2, 0, \ldots, 16\}$. For districts receiving multiple public hospitals, I use only the first treatment. Results are robust to excluding these three districts (Table B.8).

Figure 3: Effects of New Public Hospitals on Number of Private Hospitals



Note: Event study estimates from Equation 1, truncated to four pre-treatment and seven post-treatment periods. Panel A pools all 25 public hospital events. Panel B separates specialist (14 events) from non-specialist (11 events) hospitals. Each dot represents a point estimate; vertical lines show 95 percent confidence intervals. Standard errors are clustered at the district level. Full coefficient table in Table B.2.

one additional private hospital per district by year seven (Table 1, Column 2; Table B.2). In contrast, non-specialist public hospitals that are constructed in districts with essentially no pre-existing private hospitals, produce negative point estimates throughout the post-treatment period (Column 3), directionally consistent with crowd-out though imprecisely estimated after correcting for few-cluster bias (see below).

The growing pattern of effects for specialist hospitals is consistent with the physician training pipeline described in Section 2.3. The immediate effect at period zero may partly reflect the arrival of transferred specialists who staff the new hospital and the associated private investment that accompanies a major new healthcare facility. The acceleration visible around periods five and six aligns with the institutional timeline for the first residency cohorts to complete training and become available for private employment: a four-to-six year Master of Medicine program, followed by weakly enforced bond obligations that allow early departure. This growing dynamic is absent for non-specialist hospitals, which do not operate training programs and show flat near-zero effects throughout the post-treatment period.

Table 1: Average Post-Treatment Effects on Private Hospitals

	Number of Private Hospitals		
	(1)	(2)	(3)
All public hospitals	0.465		
	(0.094)		
Specialist public hospitals		0.785	
		(0.108)	
Non-specialist public hospitals			−0.171
			(0.009)
Mean Dep. Var.	1.303	1.701	0.631
Pre-Treatment Mean	1.440	2.571	0.000
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N Districts × Year	846	648	594
R^2	0.951	0.954	0.930
Events	25	14	11
Estimator	SA	SA	SA

Notes: Each column presents results from separate regressions using the Sun and Abraham (2021) interaction-weighted estimator. Coefficients represent the average of post-treatment event study coefficients. The dependent variable is the number of private hospitals in a district. Column (1) pools all public hospitals; columns (2) and (3) separate by type. Pre-Treatment Mean is the mean outcome among treated districts in the pre-treatment period. The non-specialist analytic standard error in Column (3) is anti-conservative due to concentrated treatment timing; see the bootstrap inference discussion below. Standard errors clustered at the district level in parentheses.

A standard concern with staggered event studies based on few treatment clusters is that conventional clustered standard errors can be severely anti-conservative (Cameron et al., 2008). With only 14 specialist and 11 non-specialist treatment events across 33 district clusters, I implement two alternative inference procedures that do not rely on asymptotic approximations (Section B.3). A pairs cluster bootstrap ($B = 499$) confirms the specialist result, with a 95 percent confidence interval that excludes zero. Randomization inference following Young (2019) yields a one-sided p-value of 0.06. The non-specialist result is less robust to these corrections due to concentrated treatment timing and should be interpreted as directional evidence rather than a precisely estimated standalone finding.[11]

[11] Four of the 11 non-specialist events occur in the same year, creating near-singleton event times that the analytic variance estimator treats as independent variation.

The specialist result is also robust across alternative specifications. Sensitivity analysis following Rambachan and Roth (2023) shows that the result survives post-treatment confounding up to half the magnitude of the worst pre-treatment deviation, and the pre-treatment coefficients are uniformly negative, meaning the confounding trend would need to reverse sign at treatment to overturn the positive result (Section B.7). The results hold under synthetic difference-in-differences (Table B.12), coarsened exact matching (Figure B.7), exclusion of multiple-treatment districts (Table B.8), last-treated controls (Table B.9), and across five alternative staggered DiD estimators (Table B.10). Weighting by public hospital bed capacity increases the specialist effect, consistent with training capacity scaling with hospital size (Table B.11).

4.2 Mechanism: Healthcare Utilization and Physician Supply Spillovers

To directly test the channels through which public hospitals affect private entry, I examine effects on healthcare utilization and physician supply. I draw on two data sources for the mechanism analysis. Inpatient admissions and outpatient visits by sector comes from the National Health and Morbidity Survey, a nationally representative household survey conducted in 1996, 2006, and 2011 (the most recent wave with district-level utilization data during the study period). Physician supply at the district level comes from the Malaysian Population Census of 1970, 1980, and 1991, which records occupations at sufficiently fine detail to identify specialist physicians by employment status and sector.[12] Given the limited time points in both sources, I use a stacked 2×2 difference-in-differences specification rather than the full event study design:

$$Y_{sdt} = \beta \cdot \text{Post}_t \times \text{Treated}_d + \alpha_{ds} + \lambda_{ts} + \varepsilon_{dt} \tag{2}$$

where α_{ds} are district-by-stack fixed effects and λ_{ts} are year-by-stack fixed effects. For admissions and outpatient visits, the stacks cover 1996–2006 and 2006–2011. For physicians, the stacks cover 1970–1980 and 1980–1991 (Cengiz et al., 2019; Deshpande and Li, 2019).

Healthcare Utilization and the Demand Congestion Alternative Table 2 examines whether public hospitals expand the total healthcare market or substitute for private care. Panel A shows the effects of specialist hospitals. Total inpatient admissions and total outpatient visits are essentially unchanged (Columns 1 and 3), ruling out market expansion. Instead, specialist hospitals sharply reduce private inpatient admissions by nearly half relative to the pre-treatment baseline (Column 2) and private outpatient visits by more than a third (Column 4). Panel B shows that non-specialist hospitals produce directionally similar but imprecise reductions across all utilization measures, consistent with their construction in districts with near-zero pre-treatment private activity. An important caveat is that the

[12] The 2000 census adopted revised ISCO occupation codes that combine physicians, veterinarians, dentists, and other medical professionals into a single category, precluding identification of specialist physicians. I therefore cannot measure district-level physician supply during the study period itself (1996–2013) and rely on the pre-period census evidence supplemented by contemporary registry data.

utilization data captures inpatient admissions and outpatient visits but not the full range of private hospital services. Private hospitals may respond to public competition by shifting toward elective procedures, day surgery, health screening packages, or aesthetic services that are not measured in the survey. To the extent that such service recomposition occurs, the utilization reductions reported here overstate the true demand loss faced by private entrants.

Three facts rule out the possibility that public hospitals generate excess demand that spills over to private facilities as an explanation for the specialist crowd-in. First, the utilization results show that specialist hospitals draw patients away from private facilities across both inpatient and outpatient settings, the opposite of demand spillover. Second, cross-sector referrals are negligible. Private-to-public referrals account for only 0.05 percent of public hospital admissions in 2013 administrative records.[13] Third, specialist hospitals do not increase total outpatient volume, inconsistent with a congestion channel operating through primary care.

Physician Supply The utilization results deepen the puzzle: specialist hospitals reduce private admissions by nearly half and private outpatient visits by more than a third, yet private hospitals still enter. If competition on the demand side is this strong, the supply side must offer a countervailing force. Table 3 provides direct evidence for this physician training channel, measuring the stock of physicians at the district level using census data at three-year lags from hospital construction.[14] Specialist hospitals more than double the total physician stock in treated districts (Column 1) and nearly triple the stock of private specialist physicians (Column 3). At lag 0, the immediate effect on the private specialist stock is 55 physicians; by lag 3, this grows to 108 as training cohorts graduate and transition to private practice (Table B.4). The private specialist share of total physicians rises by 28

[13]Self-reported referral sources in admission records, which likely overcount private-to-public referrals. The first formal cross-sector referral program (HSOP) was not established until 2025.

[14]The three-year lag from hospital construction to census observation captures both immediate physician recruitment (staff hired when the hospital opens) and early training cohort graduates. This is a different time horizon from the 4–7 year compulsory service bond described below, which measures time from specialist qualification to private practice transition. The lag-3 census effect reflects the net change in the district-level physician stock, which includes physicians at all stages of the training-to-transition pipeline. Table B.4 shows effects at lags 0 through 5; the stock grows monotonically as successive cohorts complete training.

Table 2: Effects of Public Hospitals on Healthcare Utilization

	Inpatient Admissions (per 10,000)		**Outpatient Visits (per 10,000)**	
	Total (1)	Private (2)	Total (3)	Private (4)
Panel A. Specialist Public Hospitals				
Post × Treated	−0.167	−0.299	0.086	−1.371
	(0.330)	(0.140)	(0.659)	(0.671)
Mean Dep. Var.	1.409	0.428	2.008	1.630
Pre-Treatment Mean	2.610	0.651	4.333	3.703
Observations	120	120	120	120
R^2	0.871	0.815	0.865	0.933
Panel B. Non-Specialist Public Hospitals				
Post × Treated	−0.369	−0.111	−0.515	−0.304
	(0.228)	(0.099)	(1.027)	(0.231)
Mean Dep. Var.	0.842	0.293	1.511	0.880
Pre-Treatment Mean	0.465	0.022	2.705	0.490
Observations	114	114	114	114
R^2	0.834	0.804	0.750	0.942
District × Stack FE	Yes	Yes	Yes	Yes
Year × Stack FE	Yes	Yes	Yes	Yes

Notes: Stacked difference-in-differences estimates using equation (2). Each column reports the average treatment effect of public hospital construction on healthcare utilization from the National Health and Morbidity Survey (1996, 2006, 2011). Columns 1–2: inpatient hospital admissions per 10,000 population. Columns 3–4: outpatient visits per 10,000 population, including both hospital outpatient departments and primary care clinics. Panel A: specialist public hospitals (14 events). Panel B: non-specialist public hospitals (11 events). Pre-Treatment Mean is the mean outcome among treated districts in the pre-treatment period. Standard errors clustered by district in parentheses.

percentage points (Column 5), from a pre-treatment mean of 38 percent. Non-specialist hospitals, which are staffed primarily by nurses and general practitioners, show no effect on any physician outcome (Columns 2, 4, 6).[15]

As a falsification test for the specificity of the labor supply channel, I examine whether specialist hospitals generate similar spillovers for other health workforce categories. Although specialist hospitals hire large numbers of nurses and health technicians to staff the new facility, none of these workers spill over to the private sector (Table B.5). This pattern is consistent with the financial incentives facing different health professions. Specialist physicians can multiply their earnings in private practice through independent clinics, hospital partnerships, and private consulting, creating strong incentives to transition once compulsory service bonds expire. Nurses and allied health workers face no comparable private-sector wage premium. Public-sector nurses in Malaysia earn slightly more than their private-sector counterparts and cannot establish independent practices, limiting both the incentive and the opportunity for public-to-private transitions.

Direct Evidence from Individual Physician Registry Data The census evidence measures the stock of physicians but cannot directly observe the flow of specialists from public training to private practice. I provide direct microeconomic evidence on this public-to-private flow using individual-level data from Malaysia's Annual Practicing Certificate (APC) registry, a mandatory annual license covering 12,503 registered specialists observed across 2023–2026.[16]

Figure 4 presents two facts supporting the mechanism. Panel A shows the share of specialists currently in private practice by qualification cohort. Among recent cohorts (2022–2024), fewer than 10 percent practice privately, consistent with the 4–7 year com-

[15]The structural model in Section 5 quantifies the relative magnitudes, showing that the physician supply effect on entry costs dominates the demand reduction. The structural model imposes $\theta_S = 54.7$ physicians from the contemporaneous (lag-0) specification in Table B.4; the lag-3 estimate reported here is larger because the training pipeline takes several years to fully mature.

[16]Specialist qualification year refers to the year in which the specialist degree (e.g., Master of Medicine) is conferred by the training institution. The APC data records each physician's primary practice location, sector (public, private, university, military), and any secondary practice locations for each year of active licensure.

Table 3: Effects of Public Hospitals on Physician Supply (3 Years Post-Construction)

	Total Physicians (100s)		**Private Specialist Physicians (100s)**		**Private Specialist Share of Total (%)**	
	(1)	(2)	(3)	(4)	(5)	(6)
Specialist	1.917		1.081		0.275	
	(1.168)		(0.471)		(0.135)	
Non-specialist		−0.236		−0.084		−0.022
		(0.267)		(0.063)		(0.015)
Mean Dep. Var.	1.145	0.536	0.411	0.141	0.218	0.093
Pre-Treatment Mean	1.500	0.000	0.571	0.000	0.375	0.000
District × Stack FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Stack FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62	66	62	66	62	66
R^2	0.863	0.923	0.858	0.880	0.940	0.985

Notes: Stacked difference-in-differences estimates using census data (1970, 1980, 1991). Effects measured 3 years post-construction to allow specialist training programs to mature; lag robustness is in Table B.4. Columns 1–2: total physicians (in 100s). Columns 3–4: private specialist physicians (in 100s), identified by self-employment status. Columns 5–6: private specialist physicians as share of total. Pre-Treatment Mean is the mean outcome among treated districts in the pre-treatment period. Non-specialist treated districts have zero pre-treatment physician counts because these hospitals are constructed in areas without existing medical infrastructure. Standard errors clustered by district in parentheses.

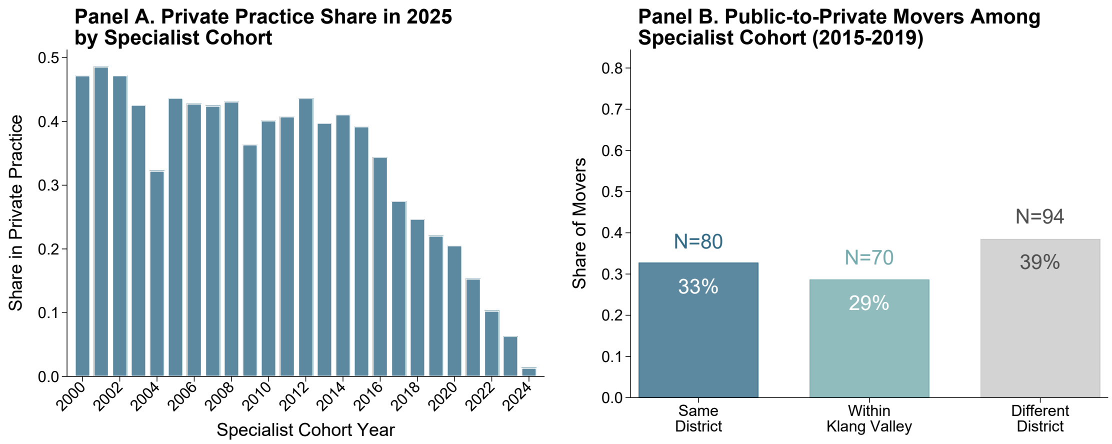
pulsory service bond following government-sponsored training.[17] As bonds expire, the private practice share rises steeply to roughly 40 percent for cohorts qualifying before 2015, indicating a long-run steady state in which two in five specialists eventually transition to private practice.

Panel B shows the geographic concentration of these transitions among 252 specialists from 2015–2019 cohorts who move from public to private practice within the observation window. One-third remain in the same district as their public posting. An additional 29 percent stay within the Klang Valley metropolitan area.[18] Together, 61 percent of movers remain in the same local labor market, supporting the interpretation that specialist hospitals expand the local supply of trained specialists who subsequently establish or join nearby private practices.

[17] Under the Medical Act 1971 and Medical Regulations 2017, specialist training through the Master of Medicine program is funded by government scholarship (*Jabatan Perkhidmatan Awam*), which carries a compulsory 4–7 year service bond in public hospitals following a 6–18 month gazettement period.

[18] The Klang Valley encompasses Kuala Lumpur, Petaling, Hulu Langat, Gombak, Klang, Putrajaya, and Kuala Langat.

Figure 4: Direct Evidence on the Public-to-Private Specialist Physician Pipeline



Note: Panel A shows the share of specialists currently in private practice by year of specialist qualification, using 12,503 registered specialists from Malaysia's Annual Practicing Certificate (APC) registry (2023–2026). The dashed vertical line marks the approximate window when 4–7 year compulsory service bonds expire. The horizontal dashed line marks the long-run steady-state private practice share of approximately 40 percent. Panel B classifies 252 public-to-private transitions among specialists from 2015–2019 qualification cohorts by geographic proximity to their last public hospital posting. The bracket indicates the combined share remaining in the same local labor market (61 percent).

The census-based physician evidence in Table 3 covers 1970–1991, predating the main study period of 1996–2013. I provide three pieces of evidence that the training channel operates throughout the study period. First, the legal framework governing physician training and public-to-private transitions has been continuous since 1971. The Medical Act 1971 (Sections 14 and 20) establishes compulsory public service and annual practicing certificate requirements that have remained in force throughout both periods. The only major amendment, in 2012, introduced a formal National Specialist Register. Before this, no specialist registration system existed, and transitions from public to private practice required only an Annual Practicing Certificate. This suggests that the pipeline was less regulated during the study period than it is today (Ismail et al., 2025).[19] Second, the APC registry data suggests the pipeline remains active in the most recent period, with roughly 40 percent of specialists eventually transitioning to private practice, though this

[19]The government scholarship system (*Hadiah Latihan Persekutuan*) that funds specialist training with a compulsory service bond has similarly operated continuously, with the first significant disruption being the introduction of contract employment in 2017—after the study period (World Bank, 2011).

contemporary rate may differ from the rate during 1996–2013 due to changes in relative public-private compensation and the expansion of private hospital capacity. Third, the upgrade falsification test below shows that capacity expansions without new training infrastructure produce muted effects during the study period, consistent with the training channel operating throughout 1996–2013. Consistent with the importance of institutional context, specialist hospitals crowded out private entry during the pre-1996 corporatization era, when the government was actively pursuing privatization and corporatization of public healthcare functions (Table B.6). During this period, uncertainty about whether public hospitals would continue to operate as public training institutions may have undermined the complementarity channel, leaving only the competitive effect on private entry.

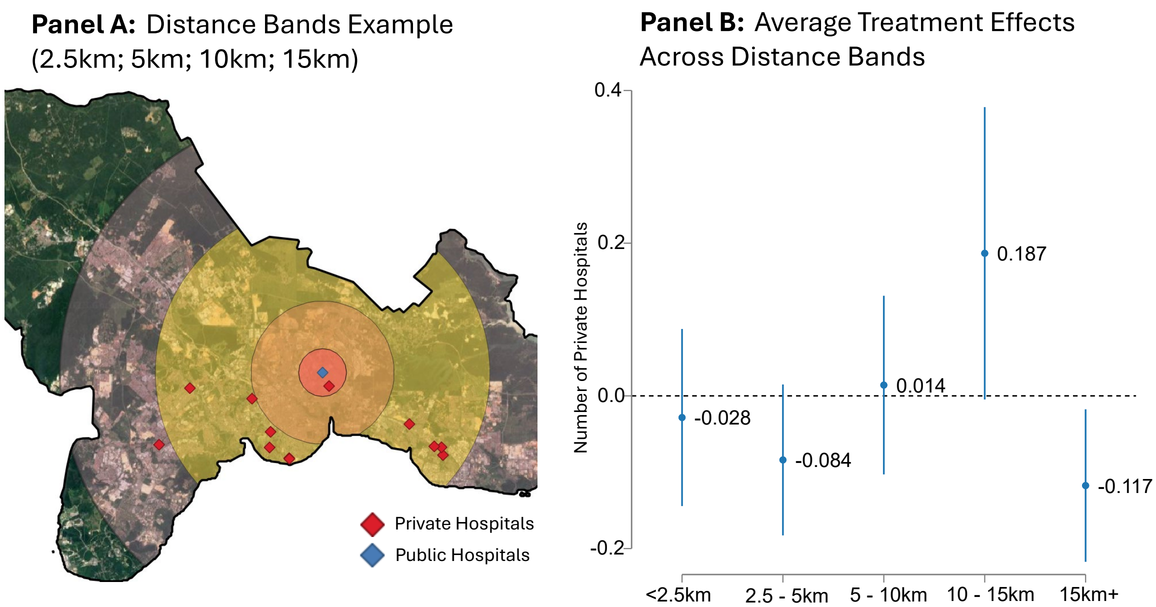
4.3 Within-District Spatial Evidence: Competition versus Complementarity

The district-level analysis shows the net effect of public hospitals on private entry, but cannot separate the competition and complementarity channels operating within a district. I exploit within-district variation in the distance between new specialist public hospitals and private entrants to test whether both forces operate simultaneously. If private entrants face both patient competition (which decays with distance from the public hospital) and physician supply complementarity (which also decays with distance, but more slowly due to physician commuting), entry should be lowest in the immediate vicinity where competition is intense, highest at an intermediate distance where the labor pool remains accessible but competition is attenuated, and decline again at greater distances where commuting costs limit physician access.

I estimate Equation 1 using the number of private hospitals within five mutually exclusive distance bands from the newly constructed specialist public hospital: 0–2.5km, 2.5–5km, 5–10km, 10–15km, and beyond 15km. The comparison group is never-treated districts, where I count all private hospitals across the entire district.

Figure 5 is consistent with the non-monotonic prediction. Private entry declines in the immediate 0–5km vicinity where patient competition with the public hospital is most intense. Entry then rises in the 10–15km band, where private hospitals can access the

Figure 5: Effects of Specialist Public Hospital on Private Entry by Distance



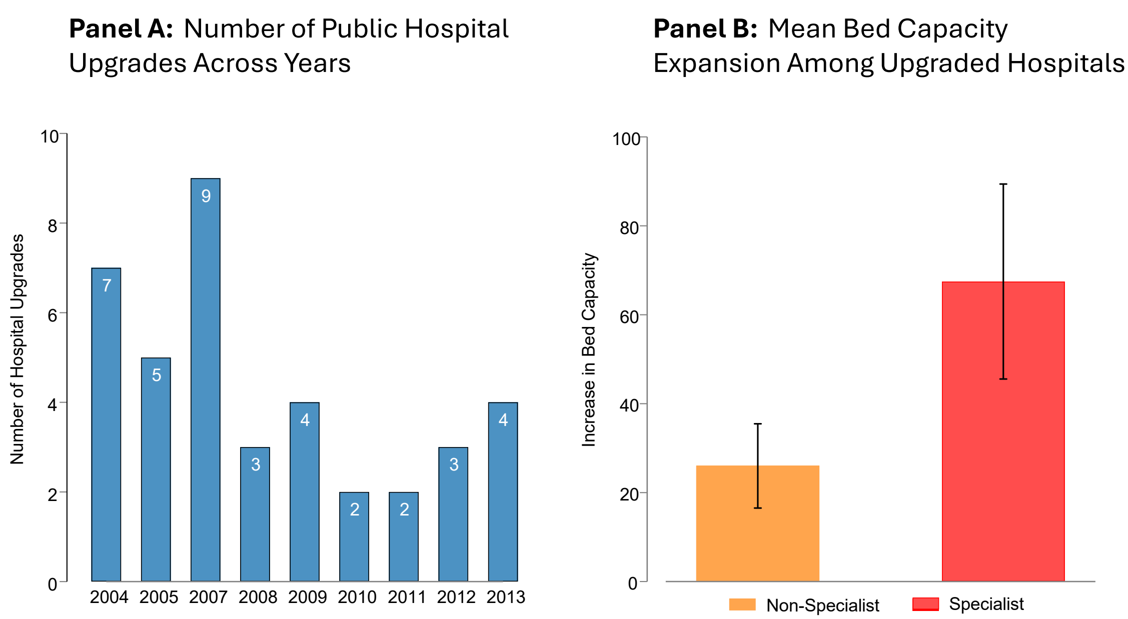
Notes: Panel A maps distance bands for the Johor Bahru district. The rings represent 2.5km, 5km, 10km and 15km from the newly constructed public hospital. Districts with multiple specialist public hospitals are omitted. Panel B plots post-treatment estimates from Equation 1 across five distance bands. The dependent variable in each regression is the number of private hospitals within the specified distance band in treated districts; the comparison group counts all private hospitals across the entire district in never-treated districts. Pre-treatment mean number of private hospitals: 0.29, 0.29, 1.43, 0.21, and 0.36 for bands 1 through 5. Standard errors clustered at the district level.

shared physician labor pool while avoiding direct patient competition. Beyond 15km, the effect turns negative again, consistent with commuting costs limiting physician access at greater distances. This spatial gradient provides within-district evidence that the district-level crowd-in reflects an interaction between competitive and complementary effects as private hospitals locate to balance proximity to the physician labor pool against patient competition.

4.4 Falsification: Hospital Upgrades

To further test the physician training mechanism, I examine an alternative treatment: public hospital upgrades that expand bed capacity without creating new training infrastructure. Unlike new construction, which creates training programs, residency positions, and specialist faculty, upgrades add beds to facilities where teaching programs already exist. If crowd-in operates through new training capacity rather than general service expansion, upgrades should produce muted effects.

Figure 6: Number of Public Hospital Upgrades by Year



Note: Hospital upgrades data are from the Ministry of Health's annual Health Facts publications, which report bed capacity at each public hospital. Upgrades are defined as year-over-year increases in bed capacity at existing public hospitals, 2003–2012.

Between 2003 and 2012, 35 public hospitals underwent significant bed capacity expansions (Figure 6). Table 4 supports the prediction: specialist upgrades produce an effect less than one-third the size of new specialist construction, and the estimate is not distinguishable from zero. Non-specialist upgrades show a negative point estimate similar to new non-specialist construction. The contrast between new construction and upgrades is consistent with the physician training mechanism: creating entirely new training infrastructure generates large physician supply spillovers, while marginally expanding existing capacity does not.

Table 4: Effects of Public Hospital Upgrades on Private Hospital Entry

	Number of Private Hospitals		
	(1)	(2)	(3)
All upgrades	0.138		
	(0.173)		
Specialist upgrades		0.238	
		(0.215)	
Non-specialist upgrades			−0.170
			(0.169)
Mean Dep. Var.	0.934	1.132	0.631
Pre-Treatment Mean	1.028	1.480	0.000
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1026	846	594
R^2	0.947	0.946	0.928
Events	35	24	11
Estimator	SA	SA	SA

Notes: Each column presents results from separate regressions examining the impact of public hospital upgrades (2003–2012) using the Sun and Abraham (2021) estimator. Hospital upgrades are defined as year-over-year increases in bed capacity, identified from the Ministry of Health's annual Health Facts publications. Control units are districts that never received upgrades. Pre-Treatment Mean is the mean outcome among treated districts in the pre-treatment period. Standard errors clustered at the district level in parentheses.

4.5 Heterogeneous Effects by Private Hospital Size

The physician supply mechanism predicts that crowd-in effects should concentrate among smaller hospitals, which require fewer specialists to reach minimum viable scale. Table 5 supports this prediction. Specialist hospitals generate large crowd-in effects on small private hospitals (fewer than 94 beds), increasing their count by roughly half relative to the pre-treatment stock, but show essentially no effect on large hospitals (Column 2). This is consistent with small hospitals benefiting most from marginal increases in the local specialist pool, while large hospitals in urban areas face relatively abundant physician supply regardless of public hospital construction. Non-specialist hospitals show directionally negative effects for both size categories (Columns 3–4), consistent with demand competition operating independently of hospital scale. Event study dynamics are in Figure B.3.

Table 5: Effects on Private Hospitals by Size

	Specialist		**Non-Specialist**	
	Small (1)	Large (2)	Small (3)	Large (4)
Post × Treated	0.727	0.057	−0.173	−0.059
	(0.085)	(0.029)	(0.005)	(0.002)
Mean Dep. Var.	0.910	0.790	0.268	0.364
Pre-Treatment Mean	1.429	1.143	0.000	0.000
Observations	648	648	594	594
R^2	0.911	0.982	0.851	0.980
Events	14	14	11	11
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Estimator	SA	SA	SA	SA

Notes: Each column presents results from separate regressions using the Sun and Abraham (2021) estimator. The dependent variable is the number of private hospitals in each size category. Small: fewer than 94 beds; large: 94 or more beds. Pre-Treatment Mean is the mean outcome among treated districts in the pre-treatment period. Standard errors clustered at the district level in parentheses.

5 Structural Model and Estimation

5.1 Overview

The reduced-form findings show that specialist public hospitals crowd in private entry through physician supply spillovers, while non-specialist hospitals crowd out entry. These estimates identify the mechanism but do not quantify its magnitude. How much does a specialist public hospital reduce the cost of private hospital entry? To answer this, I estimate a dynamic entry model in which private hospitals make forward-looking entry decisions, weighing expected profit streams against entry costs that depend on local physician supply. The model recovers the effect of physician supply on entry costs and uses it to compute the implied entry cost reduction from specialist public hospital construction.

I focus on quantifying the entry cost channel rather than simulating counterfactual hospital allocation policies. The counterfactual exercise would require strong assumptions about how the government would reallocate hospitals across districts, and about equilibrium responses in physician labor markets that I do not model. The structural model's contribution is instead to put a dollar value on the mechanism identified in the reduced form.

Figure 7: Model Timeline

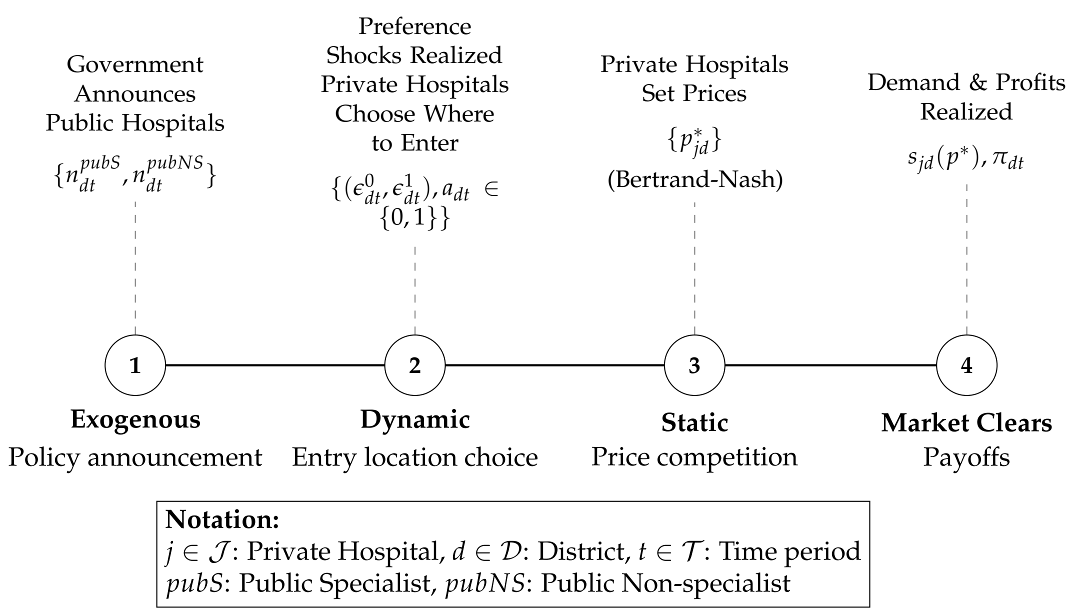


Figure 7 summarizes the timing. The government announces public hospital construction, which private entrants observe. Each potential private entrant draws an idiosyncratic cost shock and decides whether to enter a district based on anticipated profits, physician supply, population growth, and public hospital stocks. After entry, hospitals compete in prices (Bertrand-Nash), consumer demand is realized, and states evolve. I first estimate demand and compute hospital profits (Section 5.2), then estimate the dynamic entry model to recover entry costs (Section 5.3).

5.2 Demand and Hospital Profits

I estimate demand using a random coefficients logit model (Berry et al., 1995) applied to childbirth delivery services. Delivery services represent the highest-volume admission in both public and private hospitals and the only service for which I observe hospital-specific prices.[20] Consumer i choosing hospital j in district d receives utility:

$$U_{ij} = \underbrace{\alpha_{g(i)}\, p_j}_{\substack{\text{Price}\\\text{by}\\\text{income}\\\text{group}}} + \underbrace{\lambda_i\, \text{distance}_{ij}}_{\substack{\text{Travel}\\\text{disutility}}} + \underbrace{\text{private}_j \cdot (Z_i'\mathbf{\Pi})}_{\substack{\text{Preference for}\\\text{private hospitals}}} + \underbrace{H_j\beta}_{\substack{\text{Hospital}\\\text{attributes}}} + \underbrace{\xi_j}_{\substack{\text{Unobserved}\\\text{hospital}\\\text{quality}}} + \varepsilon_{ij} \tag{3}$$

Price sensitivity $\alpha_{g(i)}$ varies across income groups $g(i) = \{\text{low, mid, high}\}$, reflecting the large price gap between public hospitals (MYR 100) and private hospitals (MYR 1,500–8,000). The distance term λ_i captures that mothers prefer hospitals closer to home, which generates local market power. The private hospital interaction $Z_i'\mathbf{\Pi}$ allows preferences for private care to vary with individual characteristics including insurance status, income, and chronic disease prevalence. Hospital attributes H_j include bed occupancy rates (capturing congestion), total staff, number of medical subspecialties, and facility type indicators. The error ε_{ij} is i.i.d. Type I Extreme Value, and the outside option (traditional facilities or home births) is normalized to zero utility.

[20] Private hospitals offer maternity packages with posted prices for normal deliveries. Public hospitals charge a subsidized flat rate of MYR 100 (≈ \$24). See Figure C.7 for selected maternity promotional posters.

I estimate the model via GMM using PyBLP (Conlon and Gortmaker, 2020), combining aggregate market shares with micro moments from a national survey of families' hospital preferences. Price is instrumented using sums-of-characteristics instruments (Gandhi and Houde, 2019) with a first-stage F-statistic of 30.83. The estimation sample includes 87 private hospitals, 57 non-specialist and 55 specialist public hospitals across 95 districts.[21] Full estimation details and demand parameter estimates are in Appendix C and Table C.2. The key demand patterns are that price sensitivity decreases with income, distance deters hospital choice, and consumers with private insurance strongly prefer private hospitals.

Given the demand estimates, I recover hospital-specific marginal costs and profits from Bertrand-Nash first-order conditions. For each private hospital j, I compute profits as $\pi_j = (p_j - c_j) \cdot s_j \cdot M_d$, where p_j is the observed price, c_j is the recovered marginal cost, s_j is hospital j's predicted market share from the demand model, and M_d is the total number of births in district d. These are profits from birth deliveries alone. I scale them to total hospital profits using each hospital's ratio of birth deliveries to total admissions.[22] This scaling assumes that profit margins on birth deliveries are representative of margins across other service lines. To the extent that elective procedures or specialized services carry higher margins, total profits are understated.

For the dynamic model, I require expected profits for a potential entrant in each district beginning in 1996. The challenge is that I estimate demand from 2013 cross-sectional data but need profit expectations relevant to 1996 entry decisions. I address this by deflating 2013 prices and costs to 1996 MYR, restricting the hospital set to facilities operating by 1996, and using cross-district variation in market structure (rather than temporal trends) for identification. I construct expected entry profits $\mathbb{E}[\pi_d]$ at the district level as the share-weighted mean of incumbent profits:

$$\mathbb{E}[\pi_d] \equiv \frac{\sum_{j \in \mathcal{I}_d} s_j \, \pi_j}{\sum_{j \in \mathcal{I}_d} s_j},$$

[21] The estimation sample begins with 135 private and 135 public hospitals. After excluding facilities without obstetrics services, missing prices, or missing admissions data, 87 private hospitals remain. Full sample construction details are in Appendix C.

[22] This ratio varies from 0.06 to 0.65 across facilities (see Figure C.6).

where $\mathcal{I}_d$ denotes the set of private hospitals operating in district d by 1996, s_j are BLP demand shares, and π_j are hospital-level profits deflated to 1996 MYR.

The share-weighting assigns greater weight to incumbents with larger patient volumes. Implicitly, this assumes that an entrant's expected profits more closely approximates that of a representative incumbent than that of the marginal facility. The main alternative would be to simulate the entrant's equilibrium market share directly from the demand model, but this would require solving a full entry equilibrium for each district.

A key uncertainty is whether private entry expands the total private profit pool or simply redistributes it among more competitors. If a new entrant draws patients primarily from public hospitals or from the outside option, the total private profit pool grows with entry. If instead the entrant competes mainly with existing private hospitals, entry divides a roughly fixed pool among more firms, reducing per-hospital profits. To bound the sensitivity of the structural estimates to this uncertainty, I scale baseline profits by a parameter that captures both possibilities:

$$\mathbb{E}[\pi_d^\lambda] = \mathbb{E}[\pi_d] \cdot (1 + \lambda) \tag{4}$$

where $\lambda \in \{-0.10, 0.00, 0.10\}$ captures scenarios in which the total market profit pool contracts by 10 percent, remains unchanged, or expands by 10 percent relative to the static baseline.[23]

5.3 Dynamic Entry Model

Private hospital entry is a forward-looking investment decision. I model it as a finite-horizon dynamic discrete choice problem and estimate using the two-step approach of Bajari et al. (2007), which avoids solving the full dynamic programming problem.[24]

State Space and Entry Costs At each period t, a potential entrant in district d observes state S_{dt} and chooses $a_{dt} \in \{0, 1\}$ (wait or enter):

[23] Details on the profit construction, temporal alignment, and benchmarking against hospital group annual reports are in Section C.2.

[24] My setting involves only entry decisions without exit as no private hospital exited between 1996 and 2013. This yields a simple binary action space. No district experienced multiple entries in the same year, motivating the single-entrant restriction.

$$S_{dt} = \left(n_{dt}^{\text{pri}}, n_{dt}^{\text{pubS}}, n_{dt}^{\text{pubNS}}, \text{docs}_{dt}, \log(\text{pop}_{dt})\right) \tag{5}$$

Public hospital counts enter the state space because they affect the evolution of physician supply through the transition equation below, but they do not appear directly in the cost function. The model assumes that public hospitals affect private entry costs only through the physician supply channel, consistent with the reduced-form mechanism evidence. Entry requires paying a one-time cost that depends on local conditions:

$$\bar{C}_{dt} = \underbrace{\gamma_0 + \gamma_1 \ln(\text{pop}_{dt}) + \gamma_2 \ln(\text{LandPrice}_d)}_{\text{Sunk Costs}} + \underbrace{\gamma_3 \text{docs}_{dt}}_{\text{Operational Setup Costs}} + \delta_t \tag{6}$$

The parameter γ_3 measures how physician availability affects entry costs. The key hypothesis is $\gamma_3 < 0$. More doctors reduce entry costs by lowering physician recruitment expenses. The decomposition into sunk and operational components reflects two distinct cost channels. Sunk costs such as land acquisition and construction are paid regardless of physician supply. Operational setup costs capture the expense of assembling the initial medical team. When the local physician pool is thin, a private hospital must recruit specialists from other districts or invest in training, both of which raise entry costs. Year fixed effects δ_t capture aggregate shocks such as nationwide healthcare policy changes and macroeconomic conditions.

Value Functions The finite-horizon Bellman equation over $T = 20$ periods is:

$$V(S_{dt}) = \mathbb{E}_{\epsilon}\left[\max\left\{V^{\text{wait}}(S_{dt}) + \epsilon_{dt}^0,\ \Pi(S_{dt}) - \bar{C}_{dt} + \epsilon_{dt}^1\right\}\right] \tag{7}$$

where $(\epsilon_{dt}^0, \epsilon_{dt}^1)$ are i.i.d. Type I Extreme Value action-specific preference shocks, generating the standard logit choice probability. $\Pi(S_{dt})$ is the expected discounted profit stream from entering and $\bar{C}_{dt}$ is the deterministic entry cost from equation (6). The choice-specific values (excluding the preference shocks) are:

$$\begin{aligned} V^{\text{wait}}(S_{dt}) &= \beta \mathbb{E}[V(S_{d,t+1})] \\ \Pi(S_{dt}) &= \sum_{\tau=0}^{T-1-t} \beta^{\tau} \mathbb{E}[\pi_{d,t+\tau} \mid S_{dt}] \end{aligned} \tag{8}$$

If the firm waits, it receives no current payoff and draws a new entry opportunity next period. If it enters, it earns the discounted stream of current and future profits $\pi_{d,t+\tau}$, which evolve according to equation (9) below. The terminal condition is $V(S_{d,T}) = 0$. I set $T = 20$ to reflect a plausible investment planning horizon for healthcare infrastructure in a developing country. With $\beta = 0.95$, periods beyond year 20 receive weight $\beta^{20} \approx 0.36$, limiting the influence of the finite horizon truncation. Results are stable across $T \in \{15, 20, 25\}$ (Table C.7). Once a hospital enters, its per-period profit evolves with market conditions:

$$\pi_{dt} = \underbrace{\mathbb{E}[\pi_d^{\lambda}]}_{\substack{\text{Baseline} \\ \text{entry profit}}} \times \underbrace{\frac{\text{pop}_{dt}}{\text{pop}_{d,0}}}_{\substack{\text{Market} \\ \text{growth}}} \times \underbrace{\frac{n_{d,0}^{\text{pri}} + 1}{n_{dt}^{\text{pri}}}}_{\substack{\text{Business} \\ \text{stealing}}} \tag{9}$$

where $\mathbb{E}[\pi_d^{\lambda}]$ is the sensitivity-adjusted expected entry profit from equation (4), with $\lambda = 0$ as the baseline. $\text{pop}_{d,0}$ and $n_{d,0}^{\text{pri}}$ are the initial (1996) population and private hospital count, and n_{dt}^{pri} is the current count including subsequent entrants. The first ratio scales profits with population growth; the second captures how additional private entrants divide the market.

State Transitions Physician supply follows an AR(1) process with district fixed effects and discrete jumps at public hospital openings, estimated separately from the 1970–1991 census panel:

$$\text{docs}_{d,t+1} = \alpha_d + \rho_{\text{doc}} \cdot \text{docs}_{dt} + \theta_S \mathbb{1}\{\text{new pubS}_{dt}\} + \theta_{NS} \mathbb{1}\{\text{new pubNS}_{dt}\} + \varepsilon_{dt}^{\text{doc}} \tag{10}$$

where α_d is a district fixed effect, the estimated persistence is $\hat{\rho}_{\text{doc}} = 0.749$, $(\theta_S, \theta_{NS}) = (54.7, -6.0)$ are imposed from the contemporaneous (lag-0) reduced-form physician supply estimates (Table B.4), and $\hat{\sigma}_{\text{doc}} = 15.2$. I use the lag-0 specification rather than the larger lag-3 estimate reported in Table 3 because the forward simulation generates the gradual accumulation of physicians over time through the AR(1) process. Imposing the lag-3 estimate would double-count the pipeline's temporal dynamics. The district fixed effects anchor long-run physician supply at district-specific levels estimated from the census panel. This links the structural model directly to the reduced-form evidence. Each specialist hospital increases physician supply by 54.7, which reduces entry costs through γ_3. Population follows a similar AR(1) with district fixed effects ($\hat{\rho}_{\text{pop}} = 0.875$, $\hat{\sigma}_{\text{pop}} = 0.048$), and public hospitals follow the observed Ministry of Health construction schedule.

Estimation: Two-Step BBL In the first step, I estimate entry probabilities from a binary logit on observed entry decisions across 95 districts over 1996–2012, with doctor supply entering flexibly through quintile bins.[25] In the second step, for each district-year state I simulate $R = 500$ forward paths over a $T = 20$-period horizon under two scenarios: "enter now" and "follow the estimated CCP policy." Each simulation draws stochastic shocks for physician supply and population according to the transition equations, implements the observed public hospital construction schedule, and computes per-period profits using equation (9).[26] For the "enter now" scenario, the firm enters immediately and earns profits for all T periods. For the "wait" scenario, the firm draws entry decisions from the estimated CCPs each period. Upon entry, it begins earning profits for the remainder of the horizon. Competing private entrants also enter stochastically according to the same CCPs. Averaging across the R paths yields $\Pi(S_{dt})$ and $V^{\text{wait}}(S_{dt})$ for each initial state. The Type I Extreme Value distributional assumption yields the Hotz and Miller (1993) inversion:

[25]Estimates are in Table C.1. Private hospitals are more likely to enter areas with private specialist physicians, and less likely to enter markets with more existing public or private hospitals. The CCP estimation uses $N = 1{,}615$ district-year observations; the forward simulation uses $N = 1{,}598$ after dropping districts with missing baseline profits or fixed effects.

[26]For observations beginning after 1996, the simulation extends beyond the sample period (e.g., a 2010 observation simulates through 2029). Public hospital construction beyond the observed schedule is set to zero.

$$\kappa_{dt} \equiv \underbrace{\Pi(S_{dt}) - V^{\text{wait}}(S_{dt})}_{\Delta W_{dt}} - \underbrace{\ln\left(\frac{P(\text{enter})}{P(\text{wait})}\right)}_{\eta_{dt}} = \bar{C}_{dt} \tag{11}$$

which recovers the deterministic component of entry costs $\bar{C}_{dt}$. The intuition is direct: ΔW measures how much more profitable it is to enter now versus following the estimated CCP policy, and η reflects how likely firms are to actually enter. Districts where ΔW is high but entry is rare must have high entry costs. Districts where entry is common despite modest ΔW must have low costs. Substituting the cost function yields the second-stage regression:

$$\kappa_{dt} = \gamma_0 + \gamma_1 \ln(\text{pop}_{dt}) + \gamma_2 \ln(\text{LandPrice}_d) + \gamma_3 \text{docs}_{dt} + \delta_t + u_{dt} \tag{12}$$

I estimate this using OLS with year fixed effects and standard errors clustered at the district level. The dependent variable κ_{dt} is the revealed entry cost from forward simulation. The panel structure ($N = 1{,}598$ district-year observations across 95 districts over 1996–2012) provides both between-district variation (districts with larger physician stocks have lower entry costs relative to their profit levels) and within-district variation over time, as districts that gain physicians after specialist hospital openings experience declining entry costs.

The key parameter is γ_3, as it indicates whether physician supply reduces entry barriers, and gives the implied entry cost reduction from one specialist hospital. To address potential reverse causality (districts with higher unobserved entry potential may attract more doctors), I instrument docs_{dt} with 1980 census physician counts ($F = 36.0$).

Interpreting γ_3: Observational Equivalence Before presenting the results, I note an important interpretive point. The coefficient γ_3 captures the *total* effect of physician supply on entry incentives, regardless of whether it operates through one-time recruitment costs or capitalized ongoing labor cost savings. If physicians also reduce marginal operating costs through a thicker local labor market, the model attributes the net present value of these savings to the entry cost parameter. I show in Section C.5 that these two channels are observationally equivalent for entry decisions, and that separating them would require direct data on hospital-level input prices. The estimate of γ_3 should therefore be interpreted as the total physician supply effect on entry barriers, encompassing both recruitment and labor market channels.

5.4 Results

The identifying variation for γ_3 comes primarily from within-district changes over time. As specialist public hospitals open and train physicians, local entry costs decline. Conditional on expected profit levels, market size, and year effects, districts with greater physician supply have substantially higher private entry probability and lower revealed entry costs (Figure C.3 and Figure C.4). Mean entry costs across districts are approximately RM 5.1 million (USD 1.2 million), with mean annual profits of RM 639 thousand, implying an 8.7-year payback period (Figure C.2).[27]

Table 6: Second-Stage Entry Cost Estimates Under Alternative Profit Assumptions (Millions MYR)

	$\lambda = 0$ (Baseline)		$\lambda = -0.10$ (Contraction)		$\lambda = 0.10$ (Expansion)	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Doctors (γ_3)	−0.024	−0.027	−0.021	−0.024	−0.026	−0.030
	(0.006)	(0.012)	(0.006)	(0.010)	(0.007)	(0.013)
ln(pop)	2.357	2.707	2.122	2.436	2.593	2.978
	(1.221)	(1.627)	(1.099)	(1.465)	(1.344)	(1.790)
ln(LandPrice)	3.350	3.496	3.015	3.146	3.685	3.846
	(3.318)	(3.332)	(2.986)	(2.998)	(3.649)	(3.665)
Specialist effect (M MYR)	−1.31	−1.48	−1.18	−1.33	−1.44	−1.63
% cost reduction	26.0%	29.5%	26.0%	29.5%	26.0%	29.5%
Mean κ (M MYR)	5.02		4.52		5.52	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F	—	36.0	—	36.0	—	36.0
N	1,156		1,156		1,156	

Notes: Second-stage estimates of $\kappa_{dt} = \gamma_0 + \gamma_1 \ln(\text{pop}_{dt}) + \gamma_2 \ln(\text{LandPrice}_d) + \gamma_3 \text{docs}_{dt} + \delta_t + u_{dt}$. Dependent variable is revealed entry cost (million MYR). λ scales baseline BLP profits by $(1 + \lambda)$. Contraction ($\lambda = -0.10$) implies entry reduces the total private profit pool, expansion ($\lambda = 0.10$) captures market growth where entry draws new patients from outside options. IV uses 1980 census physician counts as an instrument (first-stage F = 36.0). Specialist effect is calculated as $\gamma_3 \times 54.7$ (physician supply increase from one specialist public hospital, lag-0 estimate from Table B.4). Percentage reduction relative to mean κ. Standard errors clustered by district in parentheses.

[27] High entry costs concentrate in rural districts lacking physicians and public hospitals. Figure C.2 maps the spatial distribution of κ across districts.

Table 6 tabulates the second-stage entry cost estimates. The baseline OLS estimate is $\gamma_3 = -0.024$ million MYR per physician (Column 1). Given that specialist public hospitals increase local physician supply by 54.7 doctors (Table B.4), this implies a reduction in private entry costs of RM 1.31 million, equivalent to 26 percent of the district mean. The IV estimate is larger ($\gamma_3 = -0.027$, Column 2), implying a 29.5 percent cost reduction and suggesting that measurement error attenuates the OLS estimates. On the broader sample without land price restrictions ($N = 1{,}598$), OLS yields $\gamma_3 = -0.028$ (approximately 30 percent cost reduction), consistent with the IV correction. The estimates are stable across profit assumptions. Whether the private profit pool contracts by 10 percent (Columns 3–4) or expands by 10 percent (Columns 5–6), the percentage cost reduction remains between 26 and 30 percent. Additional robustness checks varying the discount factor and planning horizon yield similar magnitudes (Table C.7). Forward simulation from 1996 initial conditions predicts 2012 hospital counts with a correlation of 0.947 (Figure C.11).

6 Conclusion

This paper shows that public provision can crowd in private investment when public institutions produce inputs that private firms need. In Malaysia's hospital market, specialist public hospitals that train specialist physicians through residency programs increase private hospital entry by 30 percent, while non-specialist public hospitals that lack training programs reduce entry. A dynamic entry model estimates that specialist hospitals lower private entry costs by approximately 26 percent of the district mean, operating through expanded local specialist physician supply.

The result points towards a condition under which the canonical crowd-out result reverses. When public institutions bundle service provision with the production of complementary inputs for private firms, the net effect on private investment depends on whether input complementarities exceed demand substitution. This condition is not unique to hospitals. Public universities train engineers who staff private technology firms. Public agricultural extension services develop techniques adopted by commercial farmers. Military training programs produce skilled personnel who enter private-sector aviation and logistics. In each case, whether public provision crowds in or crowds out private activity depends on the relative magnitude of the training spillover and the competitive effects. The key institutional feature is that the public sector holds a monopoly or near-monopoly on training, so that private firms cannot substitute away from the publicly trained workforce. In Malaysia, every specialist physician must complete residency in a Ministry of Health hospital regardless of where they eventually practice.

These findings connect to recent work showing that public provision can generate positive spillovers for the private sector under specific conditions. Andrabi et al. (2024) show that public school quality improvements in Pakistan raise private school quality through competitive pressure. Bergeaud et al. (2025) find that public research labs generate local R&D spillovers to private firms partly through researcher mobility. The mechanism in this paper is distinct: rather than competitive pressure or knowledge spillovers, the channel operates through a labor market in which the public sector produces a scarce input that private firms require for entry. This distinction matters for policy design, because the training spillover depends on institutional features (residency duration, bond obligations, geographic mobility of graduates) that governments can directly influence. The developing country context is particularly relevant, as public hospitals in many low- and middle-income countries serve as the primary training ground for medical professionals, the private sector delivers a growing share of patient care, and patients pay largely out of pocket.

Several limitations suggest directions for future research. First, I do not observe or model healthcare quality. If physician migration from public to private practice degrades public hospital quality, the welfare gains from private sector expansion may be offset by reduced access to specialized care for populations who rely on public facilities. Estimating the equilibrium effects on quality and access across income groups would provide a fuller welfare assessment. Second, my demand estimates focus on a single service (childbirth) that may not represent profit margins across all service lines. Third, while the structural model quantifies how physician supply affects entry incentives, I do not directly model the physician labor market. Understanding how bond length, training capacity, and geographic restrictions jointly determine the magnitude of the training spillover would clarify when governments can use public provision to stimulate complementary private investment and when the resulting physician outflow undermines the public system itself.

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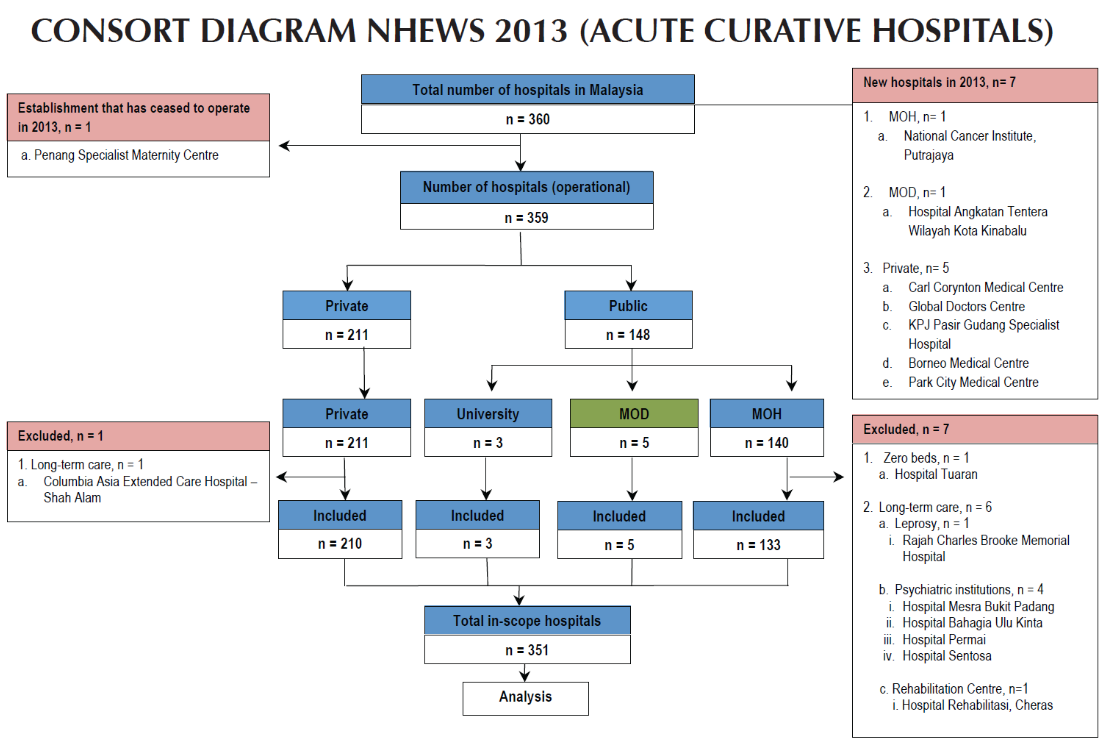
A Details on Data and Context

A.1 Hospital Panel Data Details

I have data on four years of the National Healthcare Establishment and Workforce Survey (NHEWS) (2010-2013) by the Clinical Research Centre. This survey provides me with a panel dataset of hospitals, whether the hospital provides certain services, the year in which hospitals began providing services, and year-specific levels of admission, congestion.

The survey is an initiative that gathers information on hospitals in the country concerning their services- with emphasis on specialized clinical services, facilities, medical devices, and health workforce. The NHEWS survey covers all acute curative hospitals and related specialty services for both public and private sectors. This survey asks all facilities that provide inpatient admissions in Malaysia. The survey respondent is the person-in-charge for the administrative department of hospitals. Response rates for public hospitals is 100 percent but for private hospitals it is 83.6 percent for those with less than 20 medical subspecialties and close to 90 percent for those with more than 20 medical subspecialties.

Figure A.1: Sample Details for NHEWS (2010-2013)



Notes: This figure presents sample details from the National Healthcare Establishment and Workforce Survey (NHEWS) in 2013.

A.2 Additional Survey Data Details

The National Health and Morbidity Survey is a nationally representative, two-stage (states and urban-rural status) stratified randomly sampled household survey in Malaysia. My final sample consists of respondents aged 18 and above who responded yes to the enumerator about their desire of having a child. The survey asks respondents on hypothetical choice scenarios for birth deliveries after sociodemographic questions. Specifically, the question asks:

"Which is the main health facility you would go to in the following situations?" "For birth delivery, where would you go?".

The respondent could choose exactly one from four possible responses: "government", "private", "traditional/complementary/alternative health facility" and "will not go to any facility". I chose to omit the fourth option–will not go to any facility–as the percentage of individuals answering this option is less than 0.5 percent. Following the hypothetical choice questions, the survey asks individuals on their perception of quality. The survey question asks the respondent on ratings on a 1 to 5 Likert scale, which encompasses 12 different questions of quality for outpatient care and inpatient care, in both the public and the private sector. I specifically use the questions *'Based on your perception or impression, how would you rate the government and private hospital on the following aspect ...'*. First, *'The waiting time to see a doctor once arrived at a hospital'* followed by *'Your overall impression'* Answers do not correspond to specific types of health conditions, and instead refers generally to the public and private sector.

Figure A.2: Quality Perception Survey Questionnaire

Sangat tidak bagus *Very Poor*	Tidak bagus *Poor*	Sederhana *Fair*	Bagus *Good*	Sangat bagus *Excellent*
1	2	3	4	5

(-7) TT (-9) EJ

Berdasarkan tanggapan atau kepercayaan anda [kepada penemuramah: sekiranya responden menghadapi masalah, anda boleh bantu dengan mencadangkan, e.g. Daripada perkhabaran/pengalaman keluarga, rakan-rakan anda, pengalaman anda sendiri], bagaimana anda menilai **HOSPITAL** kerajaan dan swasta (pesakit dalam) pada aspek berikut ... / *Based on your perception or impression [to interviewer: if respondent has trouble answering, you can help them by suggesting, e.g. What you hear from your relatives and friends, other's experience, own experience], how would you rate the government and private* ***HOSPITAL*** *(inpatient) on the following aspect …*

Tanya semua soalan berkenaan fasiliti Kerajaan dahulu, diikuti dengan Swasta.

		Hospital / *Hospital*	
		Kerajaan *Government*	Swasta *Private*
AC215	Kesesuaian lokasi hospital *Convenience of hospital location*		
AC216	Boleh memohon bilik persendirian / tidak berkongsi dengan ramai pesakit lain / *Ability to ask for a private room / sharing with less people*		
AC217	Keselesaan hospital (cth: kebersihan, susun atur kerusi, ruang, dll.) / *Comfort of hospital (e.g. cleanliness, setting of chairs, space, etc.)*		
AC218	Adanya ujian/ peralatan perubatan *Availability of investigations/ medical equipment*		
AC219	Adanya doktor pakar di hospital pakar *Availability of specialist (s) at the specialist hospital*		
AC220	Dibenarkan memilih doktor *Allowed to choose the doctor*		
AC221	Tempoh menunggu untuk berjumpa doktor sebaik tiba di hospital *The waiting time to see a doctor once arrived at the hospital*		
AC222	Masa yang diluangkan oleh doktor untuk pesakit *The amount of time the doctor spends with a patient*		
AC223	Kebolehan doktor memberi diagnosis dan memberi rawatan yang betul / *The ability of the doctor to give you the correct diagnosis and treatment*		
AC224	Kejelasan penerangan doktor berkenaan penyakit, ujian dan prosedur / *Clarity of doctor's explanation regarding the illness, test and procedure*		
AC225	Budi bahasa dan kesediaan doktor, penolong pegawai perubatan & jururawat untuk membantu / *Courtesy and helpfulness of doctor, assistant medical officer and nurse*		
AC226	Keberkesanan perkhidmatan / rawatan *The outcome of services / treatment*		
AC227	Caj rawatan *Treatment charges*		
AC228	Pandangan anda secara keseluruhan *Your overall impression*		

10 Borang Soal Selidik Individu Responden 13 Tahun Dan Ke Atas / *Individual Questionnaire Respondent 13 Years Old and Above*

Note: This figure shows the questions asked in the National Health and Morbidity Survey (NHMS) on quality perception for hospital services.

A.3 Additional Tables and Figures on Data and Context

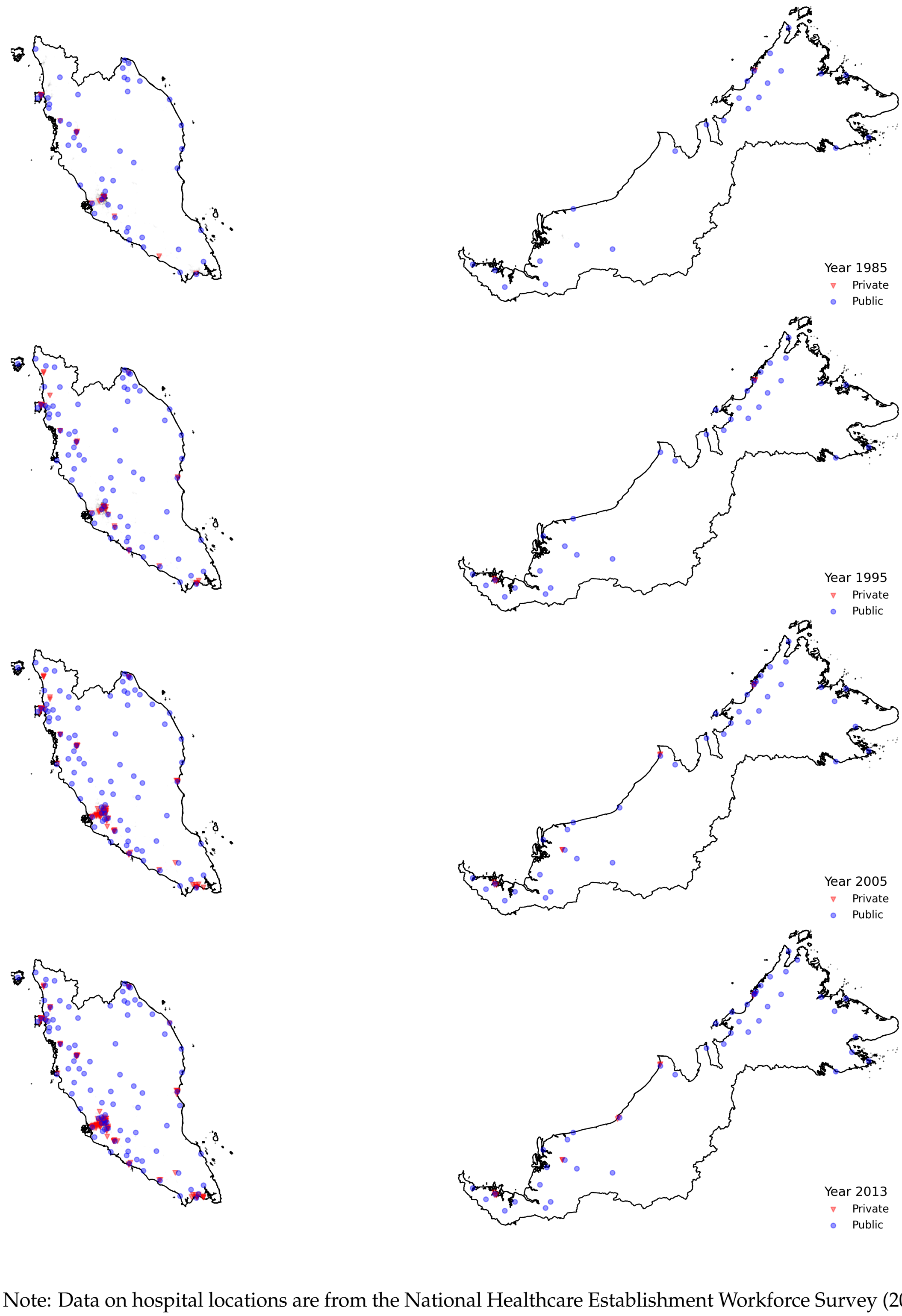
Table A.1: Summary Statistics

	Public Hospitals Specialist	Public Hospitals Non-Specialist	Private Hospitals
A. Hospital Characteristics (2013)			
N Hospitals	61	74	134
Avg. Physician	226.39	12.36	34.89
Avg. Other Staff	719.79	80.91	133.29
Avg. Beds	509.08	88.80	94.06
Avg. Inpatient Admissions	34,291	5,432	8,395
Avg. Outpatient Visits	96,276	52,539	28,116
Avg. Bed Occupancy Rate (%)	73.9	47.33	53.88
Ownership Group (%)			
Government	61 (100%)	74 (100%)	-
Independent	-	-	87 (65%)
Columbia Asia	-	-	11 (8%)
KPJ	-	-	22 (16%)
Pantai	-	-	11 (8%)
Sime Darby	-	-	3 (2%)
B. Maternity Services			
Avg. Vaginal Deliveries	3,176	586	589
Avg. District Market Share (Deliveries)	0.70	0.79	0.08
Price (MYR)	100	100	3,306

	Survey Data: Public Hospitals	Survey Data: Private Hospitals
C. Survey Data		
Indv. Monthly Income (MYR)	1.52	2.54
Distance Public (km)	13.17	10.28
Distance Private (km)	31.82	15.31
Private Insurance	0.16	0.52
Chronic Disease	0.70	0.61
Quality Rating (1-5)	4.03	3.83
Wait Time Satisfaction	3.23	3.82

Notes: Panel A shows characteristics for 269 hospitals from the National Healthcare Establishment and Workforce Survey (NHEWS). Panel B presents maternity service statistics for normal vaginal deliveries from Ministry of Health electronic health records (SMRP for public, PHDD for private hospitals). Public hospital prices reflect standardized subsidized rates for third-class wards. Private hospital prices are minimum advertised rates from primary data collection (websites, social media, direct contact). Panel C shows stated preferences from 15,296 families with childbearing intentions in the National Health and Morbidity Survey (NHMS) 2015, split by hospital type preference. Distance measured as straight-line distance from households to nearest hospital within each district. Income in thousands of MYR. Quality rating and wait time satisfaction on 1-5 Likert scales.

Figure A.3: Public and Private Hospital Locations (1982-2013)

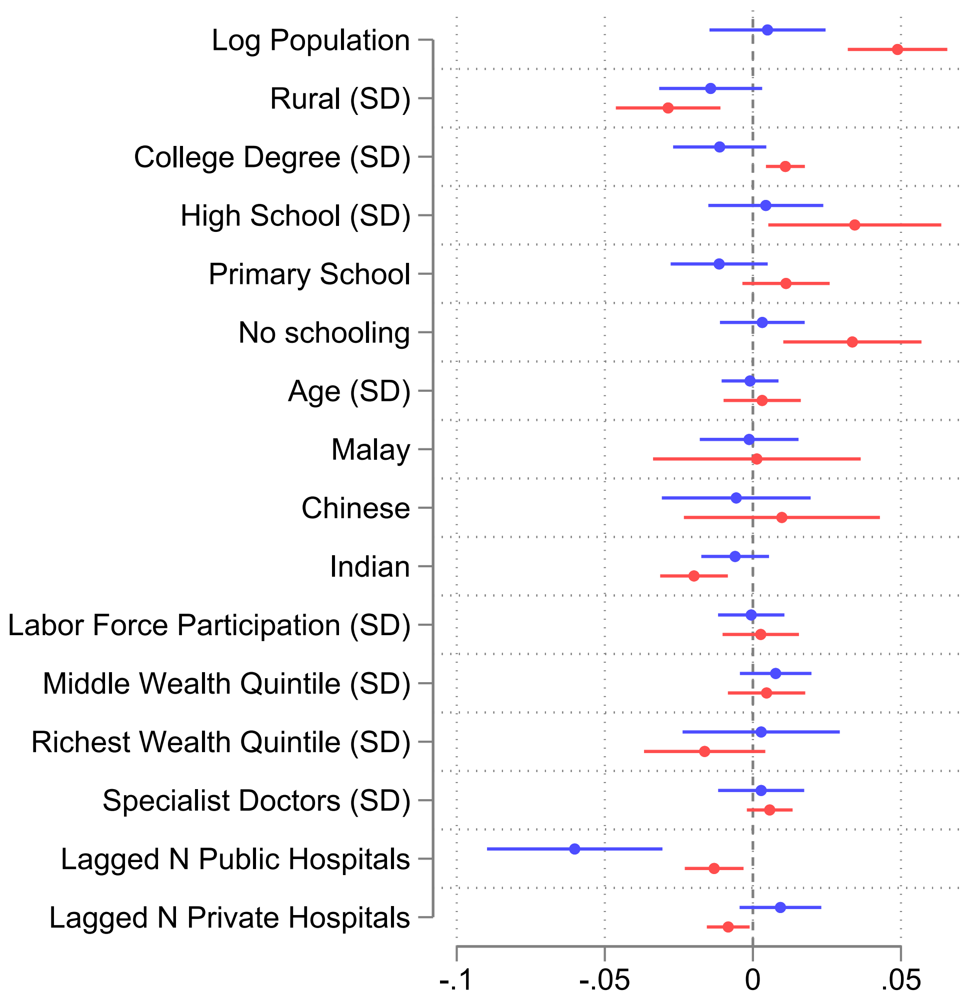


Note: Data on hospital locations are from the National Healthcare Establishment Workforce Survey (2013). This figure shows the locations of public and private hospitals in Malaysia from 1982 to 2013.

Figure A.4: Example Hospital Images

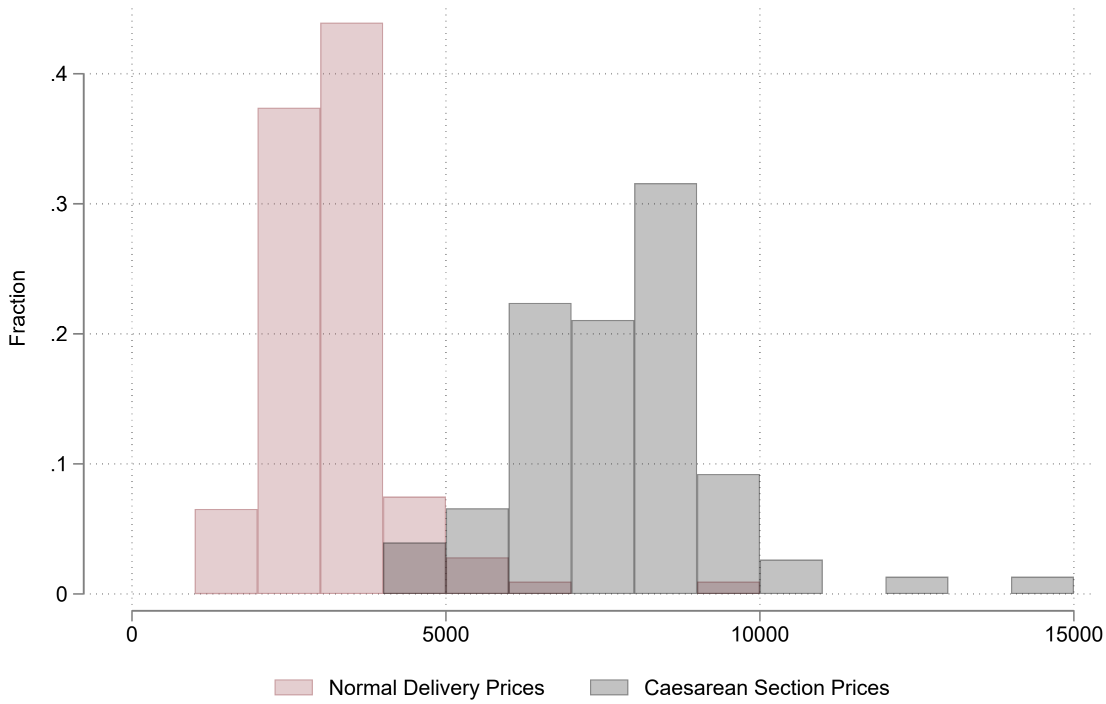
Note: These panels show examples of what hospitals in Malaysia look like based on their categories.

Figure A.5: Determinants of Public and Private Hospital Entry (Full Coefficient Set)



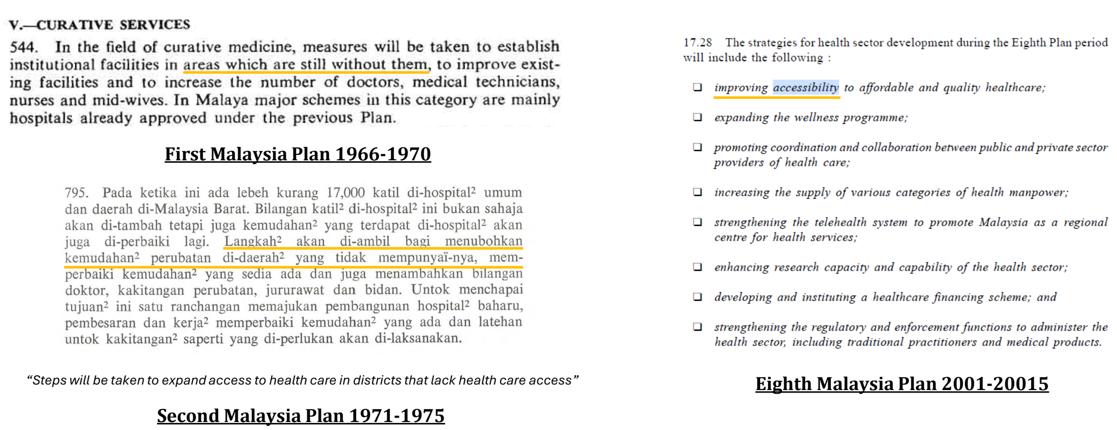
Note: These coefficients are average marginal effects from logit regressions with year fixed effects of public (or private) hospital entry on a set of district characteristics.

Figure A.6: Distribution of Birth Delivery Prices in Private Hospitals (MYR)



Note: This figure shows the distribution of normal (vaginal) delivery and caesarean section prices in private hospitals in Malaysia. Most maternity packages offer only normal delivery packages, but some private hospitals do offer caesarean section packages as well.

Figure A.7: Selected Excerpts from Malaysia Planning Documents



V.—CURATIVE SERVICES

544. In the field of curative medicine, measures will be taken to establish institutional facilities in areas which are still without them, to improve existing facilities and to increase the number of doctors, medical technicians, nurses and mid-wives. In Malaya major schemes in this category are mainly hospitals already approved under the previous Plan.

First Malaysia Plan 1966-1970

795. Pada ketika ini ada lebeh kurang 17,000 katil di-hospital[2] umum dan daerah di-Malaysia Barat. Bilangan katil[2] di-hospital[2] ini bukan sahaja akan di-tambah tetapi juga kemudahan[2] yang terdapat di-hospital[2] akan juga di-perbaiki lagi. Langkah[2] akan di-ambil bagi menubohkan kemudahan[2] perubatan di-daerah[2] yang tidak mempunyaï-nya, memperbaiki kemudahan[2] yang sedia ada dan juga menambahkan bilangan doktor, kakitangan perubatan, jururawat dan bidan. Untok menchapai tujuan[2] ini satu ranchangan memajukan pembangunan hospital[2] baharu, pembesaran dan kerja[2] memperbaiki kemudahan[2] yang ada dan latehan untok kakitangan[2] saperti yang di-perlukan akan di-laksanakan.

"Steps will be taken to expand access to health care in districts that lack health care access"

Second Malaysia Plan 1971-1975

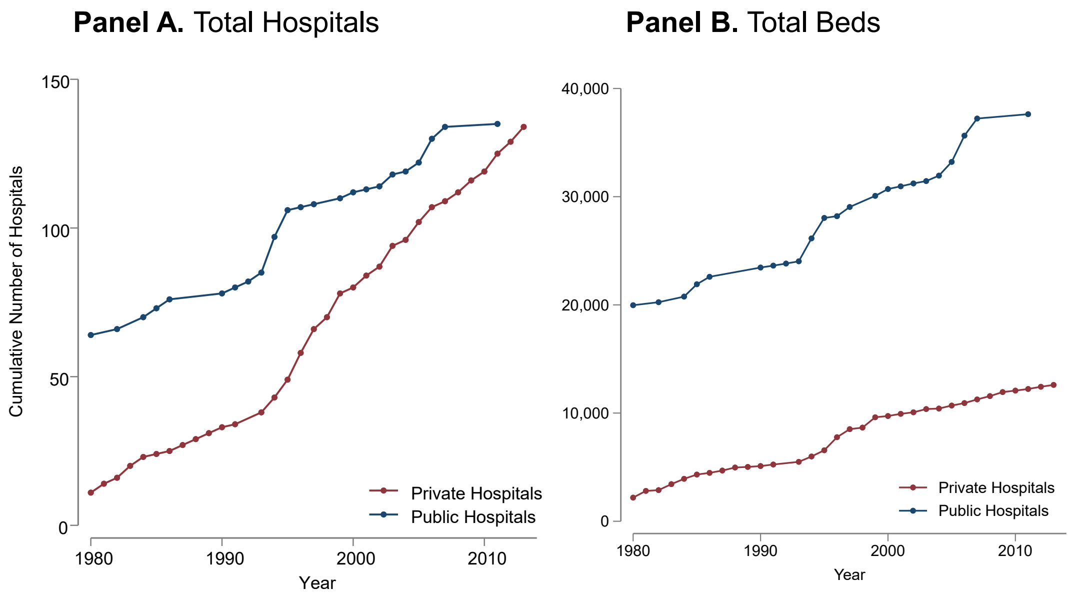
17.28 The strategies for health sector development during the Eighth Plan period will include the following :

- *improving accessibility to affordable and quality healthcare;*
- *expanding the wellness programme;*
- *promoting coordination and collaboration between public and private sector providers of health care;*
- *increasing the supply of various categories of health manpower;*
- *strengthening the telehealth system to promote Malaysia as a regional centre for health services;*
- *enhancing research capacity and capability of the health sector;*
- *developing and instituting a healthcare financing scheme; and*
- *strengthening the regulatory and enforcement functions to administer the health sector, including traditional practitioners and medical products.*

Eighth Malaysia Plan 2001-20015

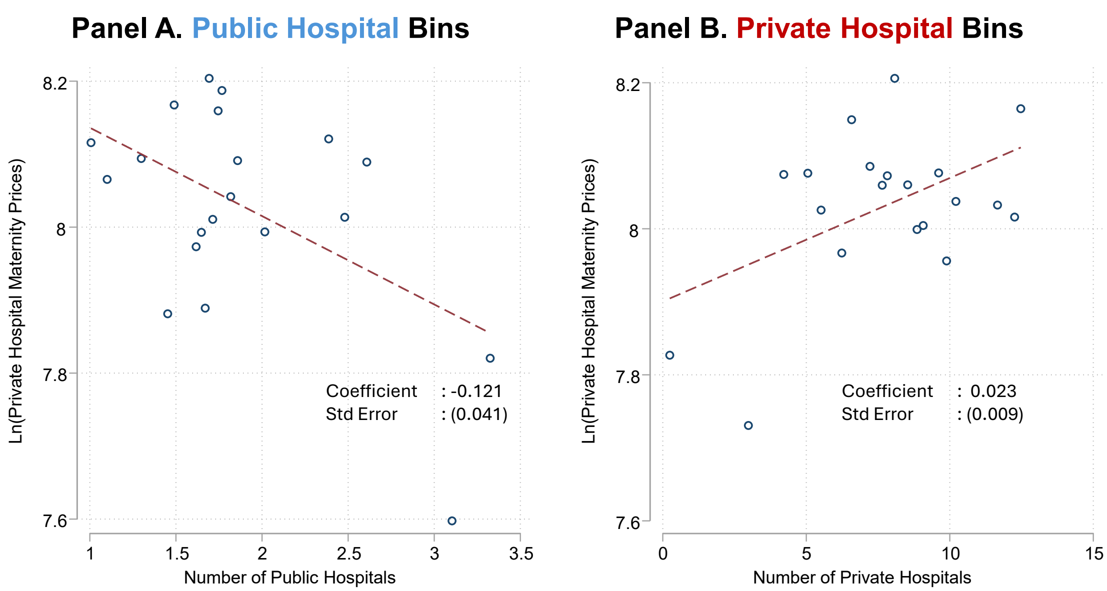
Note: These excerpts are taken from various planning documents related to healthcare development in Malaysia. These panels show the commitment of the Malaysian government in prioritizing access to healthcare.

Figure A.8: Total Count and Beds by Public and Private Hospitals



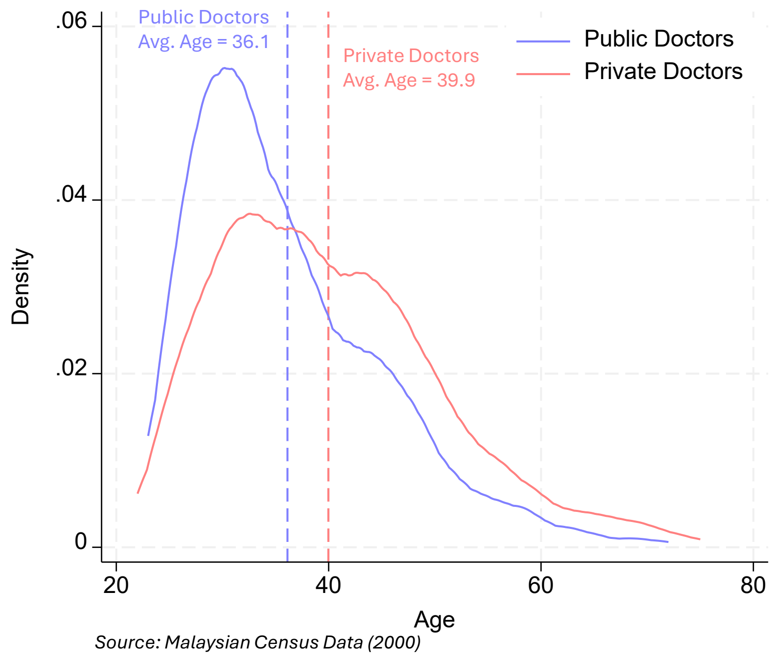
Note: This figure shows the total count of hospitals and the number of beds available in public and private hospitals in Malaysia between 1980 and 2014.

Figure A.9: Private Hospital Normal Delivery Prices by Number of Public/Private Hospitals in District



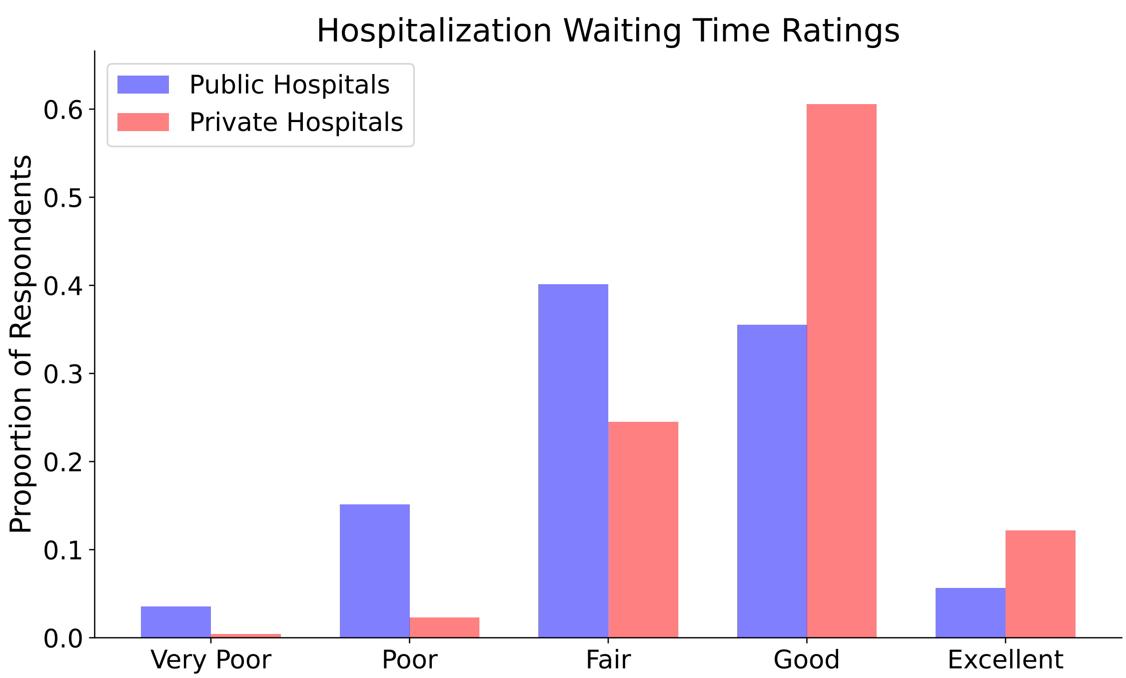
Note: Panel A figure shows a binscatter of private hospital normal delivery prices against the number of public hospitals within the same district. Panel B shows a binscatter against the number of private hospitals within the same district. This figure shows descriptive evidence on public competitive pressures on private pricing.

Figure A.10: Physician Average Age by Public & Private Hospitals



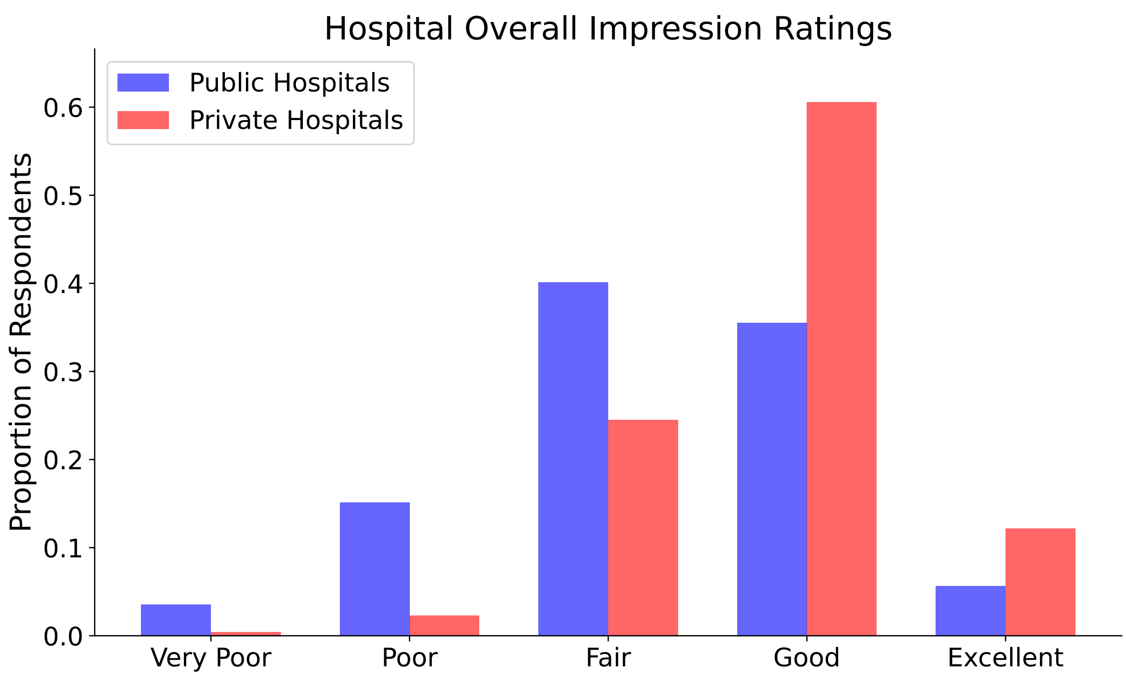
Note: This figure shows the average age of physicians working in public and private hospitals in Malaysia. The difference is approximately 3.8 years. This roughly coincides with the four-year mandatory service obligation in the public sector.

Figure A.11: Survey Waiting Time Ratings by Public & Private Hospitals



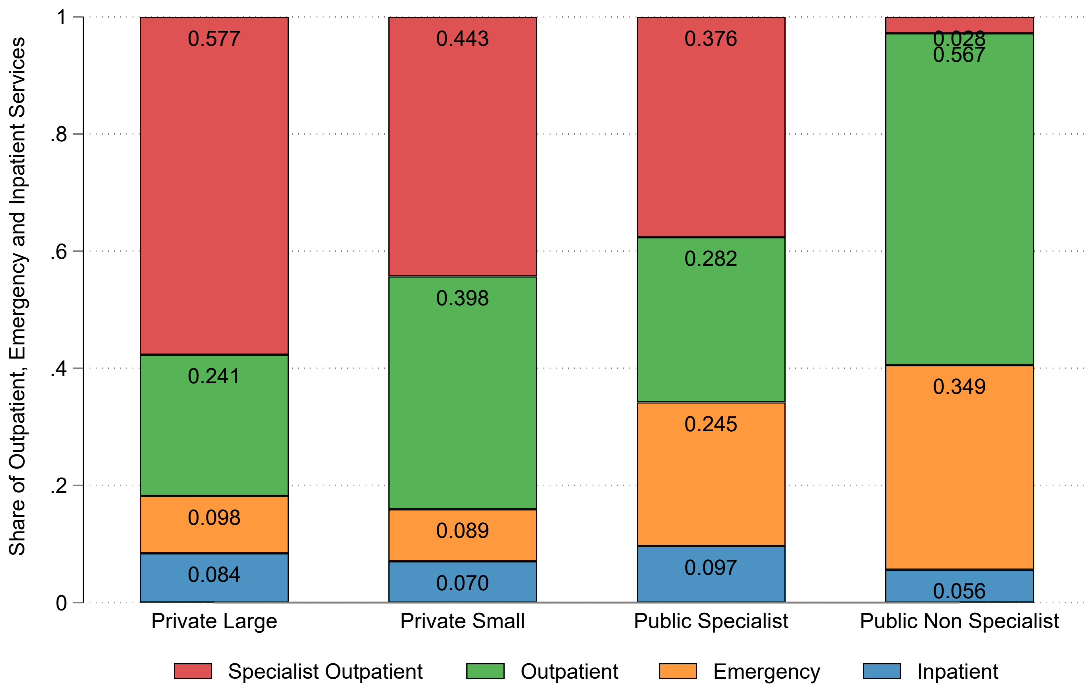
Note: This figure shows survey respondents' ratings of waiting times at public and private hospitals in Malaysia from the National Health and Morbidity Survey 2015.

Figure A.12: Hospital Overall Ratings by Public & Private Hospitals



Note: This figure shows survey respondents' overall ratings of public and private hospitals in Malaysia from the National Health and Morbidity Survey 2015.

Figure A.13: Proportion of Outpatient, Emergency and Inpatient Visits at Private and Public Hospitals

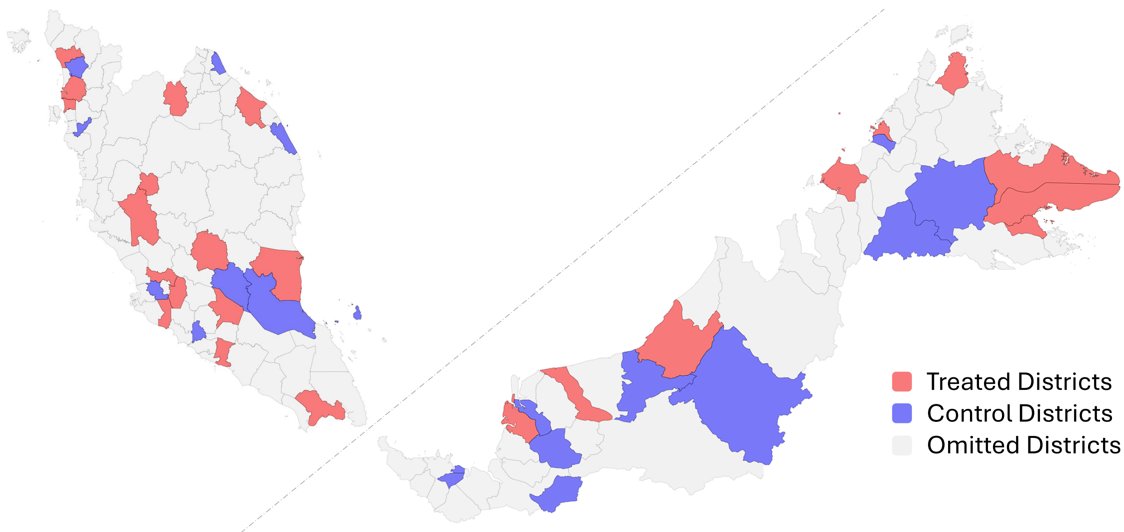


Note: Data from the National Healthcare Establishment Workforce Survey (2013). Panels show the distribution of outpatient, emergency, and inpatient visits across public and private hospitals.

B Further Details on Reduced Form

B.1 Balance and Sample

Figure B.1: Sample of Districts in Event Studies



Note: Red districts are included in the event study design as treated districts, while blue districts are controls. Grey districts are omitted from the event study.

Table B.1: Pre-Treatment Summary Statistics by Treatment Status in 1996

Variable	Treated	Never Treated	Difference	P-value
Panel A. Demographics				
Log Population	11.754 (1.115)	11.057 (1.106)	0.697	0.037
Rural Population Share	0.602 (0.310)	0.782 (0.312)	-0.180	0.063
Average Age	23.717 (2.043)	25.258 (2.536)	-1.541	0.031
Female Share	0.482 (0.024)	0.497 (0.039)	-0.015	0.123
Chinese Share	0.215 (0.151)	0.200 (0.194)	0.015	0.773
Malay Share	0.416 (0.306)	0.447 (0.354)	-0.031	0.752
Indian Share	0.071 (0.080)	0.047 (0.063)	0.024	0.281
Labor Force Participation	0.632 (0.058)	0.642 (0.104)	-0.010	0.669
Panel B. Socioeconomic Status				
Poorest	0.434 (0.260)	0.494 (0.286)	-0.060	0.476
Middle	0.307 (0.129)	0.293 (0.153)	0.014	0.733
Richest	0.258 (0.181)	0.213 (0.205)	0.045	0.446
Panel C. Education				
College/University	0.021 (0.020)	0.021 (0.033)	0.000	0.968
Secondary Completed	0.226 (0.080)	0.222 (0.079)	0.004	0.867
Primary Completed	0.201 (0.041)	0.194 (0.041)	0.007	0.617
Some Primary Education	0.201 (0.030)	0.204 (0.034)	-0.003	0.766
Panel D. Health Facilities				
Dist. to Pub Hosp (km)	36.522 (28.627)	41.423 (40.336)	-4.901	0.630
Dist. to Pri Hosp (km)	102.979 (105.322)	106.691 (112.125)	-3.712	0.907
N Public Hospitals	0.320 (0.557)	0.182 (0.395)	0.138	0.338
N Private Hospitals	0.680 (1.725)	0.273 (0.935)	0.407	0.329
N Specialist Physicians	0.050 (0.111)	0.018 (0.058)	0.032	0.266

Notes: This table compares the 25 treatment districts with the 22 never treated districts based on pre-treatment characteristics in 1991. Standard deviations in parentheses. Unit of observation is districts. All data from the 1991 Malaysian Census and hospital panel data. Distances are straight-line kilometers to facilities from 1km grids, collapsed at the district level. Wealth quintiles are constructed from household assets (electricity, water supply, telephone, automobiles, air conditioning, washing machine, refrigerator, television, VCR, radio, toilet, wall material).

B.2 Full Event Study Coefficients

Table B.2 reports the full set of event study coefficients from Equation 1, corresponding to the truncated figure in the main text (Figure 3).

Table B.2: Dynamic Effects of Public Hospital Construction (Full Coefficient Table)

Time since Construction	(1) All Public Hospitals	(2) Specialist Public Hospitals	(3) Non-Specialist Public Hospitals
-10	-0.314	-1.190	0.415
	(0.041)	(0.293)	(0.087)
-9	-0.075	-0.527	0.315
	(0.073)	(0.215)	(0.071)
-8	-0.059	-0.329	0.214
	(0.069)	(0.237)	(0.068)
-7	-0.012	-0.310	0.224
	(0.077)	(0.228)	(0.060)
-6	-0.058	-0.286	0.150
	(0.067)	(0.211)	(0.044)
-5	-0.030	-0.166	0.109
	(0.048)	(0.144)	(0.043)
-4	-0.048	-0.130	0.055
	(0.048)	(0.132)	(0.041)
-3	-0.035	-0.090	0.031
	(0.036)	(0.084)	(0.043)
-2	-0.047	-0.077	-0.012
	(0.027)	(0.084)	(0.040)
0	0.082	0.200	-0.070
	(0.048)	(0.095)	(0.034)
1	0.094	0.244	-0.101
	(0.051)	(0.107)	(0.037)
2	0.142	0.355	-0.132
	(0.056)	(0.135)	(0.032)
3	0.127	0.332	-0.134
	(0.058)	(0.140)	(0.032)
4	0.155	0.387	-0.145
	(0.066)	(0.167)	(0.032)
5	0.171	0.436	-0.169
	(0.078)	(0.198)	(0.038)
6	0.344	0.766	-0.198
	(0.123)	(0.261)	(0.039)
7	0.421	0.861	-0.169
	(0.148)	(0.326)	(0.016)
8	0.179	0.392	-0.209
	(0.195)	(0.317)	(0.024)
9	0.213	0.445	-0.261
	(0.223)	(0.345)	(0.030)
10+	0.323	0.673	-0.295
	(0.313)	(0.481)	(0.020)
Observations	846	648	594
R-squared	0.965	0.970	0.946

Standard errors in parentheses, clustered at the district level.

B.3 Alternative Inference Procedures

With 14 specialist treatment events and 33 district clusters, conventional clustered standard errors may understate uncertainty. I implement two alternative inference procedures that do not rely on asymptotic approximations.

Pairs Cluster Bootstrap. Standard clustered standard errors assume that as the number of clusters grows large, the sampling distribution of the estimator converges to a normal distribution. With only 33 clusters, this approximation may be poor: the analytic formula could understate the true variability of the estimates across different realizations of the data. The pairs cluster bootstrap directly estimates this variability by repeatedly resampling the data and computing the statistic each time, rather than relying on the asymptotic formula.

Specifically, I resample entire districts (not individual observations) with replacement ($B = 499$), preserving the within-district correlation structure, and re-estimate the Sun and Abraham (2021) specification on each draw (Cameron et al., 2008). Each bootstrap draw produces a new estimate of the average post-treatment effect. The standard deviation of these 499 estimates is the bootstrap standard error. The one-sided percentile p-value is the share of bootstrap estimates that fall below zero, and the 95 percent confidence interval is constructed from the 2.5th and 97.5th percentiles of the bootstrap distribution.

Table B.3 reports the results. For the specialist result, the bootstrap standard error is approximately three times the analytic standard error (0.356 versus 0.108), with a one-sided percentile p-value of 0.04 and a 95 percent confidence interval of [0.053, 1.474]. The specialist result therefore remains statistically distinguishable from zero even under this more conservative procedure. The bootstrap standard error for the non-specialist result inflates by a factor of 17 (0.158 versus 0.009), reflecting the fact that four of the 11 non-specialist events occur in the same year. The analytic standard error of 0.009 is therefore severely anti-conservative for this specification as the bootstrap-corrected standard error is 0.158.

Randomization Inference. Randomization inference asks a different question than the bootstrap. Rather than asking whether the standard errors are correctly sized, it asks: could an effect this large have arisen by chance, simply because the 14 treated districts happened to be places where private hospitals were growing for reasons unrelated to public hospital construction? The test answers this by asking what the estimated effect would look like if treatment had been randomly assigned to a different set of 14 districts.

Under the null hypothesis of no treatment effect, I randomly select 14 of the 36 total districts (14 treated plus 22 never-treated), assign them the original vector of treatment years, and designate the remaining 22 as never-treated controls (Young, 2019). I then re-estimate the Sun-Abraham specification and store the average post-treatment coefficient. Repeating this 999 times generates a distribution of placebo effects under the null. If the actual estimate is unusually large relative to this distribution, treatment assignment matters.

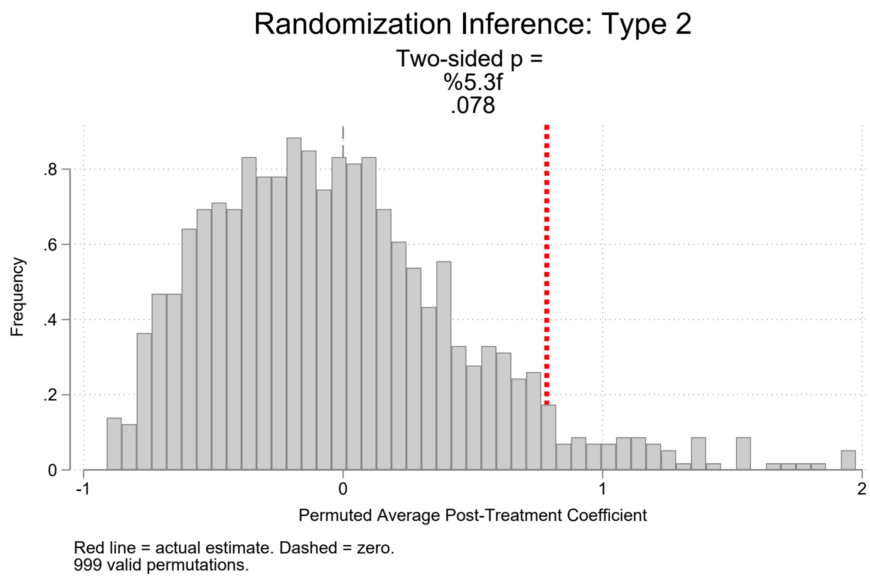
Figure B.2 shows the result. The permutation distribution is centered near zero (mean $= -0.026$, SD $= 0.495$), showing the test has power against the null. The actual specialist estimate of 0.785 lies in the right tail, with a one-sided p-value of 0.06 and a two-sided p-value of 0.08. The RI p-value exceeds the bootstrap p-value (0.04) because the two procedures answer different questions. The bootstrap asks whether the analytic standard error understates the true sampling variability for the actual set of treated districts. The RI asks whether the entire estimated effect could arise from chance assignment of treatment across districts, including the possibility that some random selections of 14 districts could exhibit strong secular private hospital growth even absent treatment. As a complementary diagnostic, permuting treatment timing among the 14 treated districts while keeping the set of treated districts fixed yields a p-value of 0.46, indicating that treatment effects are homogeneous across cohorts and consistent with the near-identical Sun-Abraham and TWFE estimates (Table B.7).

Table B.3: Alternative Inference for Average Post-Treatment Effects

	All (1)	Specialist (2)	Non-specialist (3)
Panel A. Main Table Result (Clustered)			
Coefficient	0.465	0.785	-0.171
Standard error	(0.094)	(0.108)	(0.009)
Panel B. Pairs Cluster Bootstrap ($B = 499$)			
Bootstrap SE	0.341	0.356	0.158
SE inflation	3.6×	3.3×	16.7×
Percentile p-value (one-sided)	0.180	0.040	0.084
95% CI	[-0.227, 1.080]	[0.053, 1.474]	[-0.570, 0.000]
Panel C. Randomization Inference ($B = 999$)			
One-sided p-value	—	0.060	—
Two-sided p-value	—	0.078	—

Notes: Panel A reports analytic standard errors clustered at the district level from Table 1. Panel B reports pairs cluster bootstrap results that resample entire districts with replacement. Panel C reports randomization inference p-values from permuting treatment status across all 36 districts (14 treated, 22 never-treated), preserving the original treatment year vector. RI is reported only for the specialist specification (Column 2), which is the paper's main result.

Figure B.2: Randomization Inference Distribution for Specialist Hospital Effects



Notes: Distribution of average post-treatment coefficients from 999 permutations that randomly assign 14 of 36 districts to treatment status. The red vertical line marks the actual estimate (0.785). The dashed line marks zero. The permutation distribution is centered near zero (mean $= -0.026$), showing the test has power against the null. One-sided p-value: 0.06; two-sided p-value: 0.08.

B.4 Physician Supply: Lag Robustness

The physician supply mechanism operates with a delay: residency training in Malaysia requires four to six years, followed by a compulsory service bond of four to seven years. The main physician results in Table 3 use lag 3 (approximately one census decade) to capture accumulated effects over a training cycle. The structural model instead imposes $\theta_S = 54.7$ from the lag-0 estimate, because the AR(1) transition equation generates the gradual buildup of physicians endogenously through persistence ($\hat{\rho} = 0.749$); imposing a longer-lag estimate would double-count the pipeline dynamics.

Table B.4 reports the effects across lag lengths 0 through 5. For specialist hospitals (Panel A), the effect grows monotonically from 0.547 at lag 0 to 1.081 at lag 3, where it stabilizes. This pattern is consistent with the training timeline: the contemporaneous jump (lag 0) reflects the arrival of specialists who staff the new hospital, while the growth through lags 1–3 captures the first cohorts completing residency training and entering private practice. The stabilization at lag 3 suggests the pipeline reaches a steady state within approximately one training cycle. For non-specialist hospitals (Panel B), the effects are close to zero and statistically insignificant at all lags, showing that the physician supply channel is specific to hospitals with training programs.

Table B.4: Robustness: Effects of Public Hospitals on Private Specialists by Lag Length

	Private Specialist Physicians (100s)					
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Panel A: Specialist Public Hospitals						
Number of Hospitals	0.547	0.772	0.743	1.081	1.081	1.081
	(0.302)	(0.477)	(0.391)	(0.471)	(0.471)	(0.471)
Observations	58	58	60	62	62	62
Mean Dep. Var.	0.309	0.378	0.375	0.411	0.411	0.411
R^2	0.872	0.891	0.891	0.858	0.858	0.858
Panel B: Non-Specialist Public Hospitals						
Number of Hospitals	0.063	0.063	-0.084	-0.084	-0.088	-0.093
	(0.158)	(0.158)	(0.063)	(0.063)	(0.066)	(0.074)
Observations	68	68	66	66	68	68
Mean Dep. Var.	0.159	0.159	0.141	0.141	0.137	0.137
R^2	0.820	0.820	0.880	0.880	0.881	0.881

Notes: Each column presents stacked difference-in-differences estimates with different lag structures. The main physician supply results (Table 3) use lag 3. The structural model (Section 5) imposes $\theta_S = 54.7$ from the lag-0 estimate, which captures the contemporaneous physician supply jump used in the AR(1) transition equation. Effects for specialist hospitals strengthen at longer lags, consistent with residency training programs requiring several years to graduate specialists who then enter private practice. Panel A: specialist public hospitals. Panel B: non-specialist public hospitals. All specifications include district-by-stack and year-by-stack fixed effects. Standard errors clustered at the district level in parentheses.

B.5 Effects on Other Health Workforce Categories

Table B.5 tests whether the labor supply spillover extends beyond specialist physicians to other health workforce categories. Specialist hospitals generate large increases in total nursing staff and health technicians employed at the new facility (Columns 1–2), but none of these workers spill over to the private sector (Columns 3–4). Although nurses and allied health workers are trained in the public sector alongside physicians, the financial incentives for public-to-private transitions differ sharply across professions. Specialist physicians can multiply their earnings through independent private practice, hospital partnerships, and consulting. Nurses and health technicians face no comparable private-sector wage premium as public-sector nurses in Malaysia earn slightly more than their private-sector counterparts. Also, nurses and health technicians cannot establish independent practices, limiting both the incentive and the opportunity for transitions. The null effects on private-sector nurses and health technicians therefore serve as a falsification test, showing that the labor supply channel operates specifically through the specialist physician training pipeline rather than through a general public-sector workforce expansion.

Table B.5: Effects of Public Hospitals on Nurses and Health Technicians (100s)

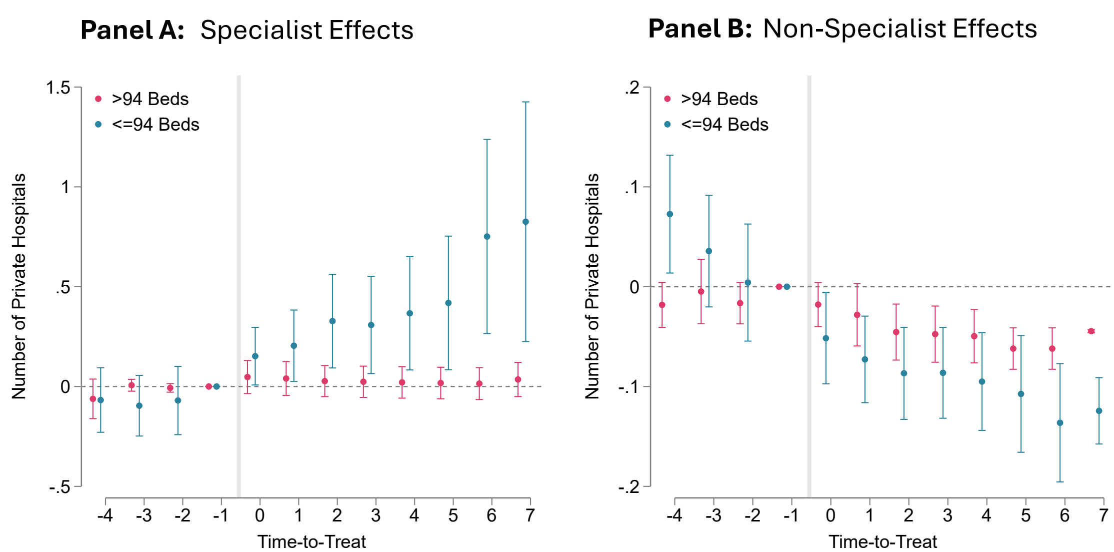
	Total		**Private**	
	Specialist (1)	Non-spec. (2)	Specialist (3)	Non-spec. (4)
Panel A. Nurses and Midwives (100s)				
Post × Treated	4.373	−0.640	0.102	−0.033
	(2.377)	(0.574)	(0.109)	(0.034)
Mean Dep. Var.	4.654	2.360	0.092	0.061
Pre-Treatment Mean	6.944	0.333	0.056	0.000
Observations	120	114	120	114
R^2	0.919	0.962	0.775	0.844
Panel B. Health Technicians (100s)				
Post × Treated	10.593	−1.747	0.288	−0.179
	(5.493)	(1.451)	(0.237)	(0.102)
Mean Dep. Var.	5.254	2.943	0.196	0.145
Pre-Treatment Mean	3.611	0.333	0.000	0.000
Observations	120	114	120	114
R^2	0.748	0.854	0.760	0.841
District × Stack FE	Yes	Yes	Yes	Yes
Year × Stack FE	Yes	Yes	Yes	Yes

Notes: Stacked difference-in-differences estimates using census data (1970, 1980, 1991). Dependent variables are in hundreds. Nurses and midwives identified by ISCO-68 codes 71 and 73 (ISCO-88 code 323). Health technicians identified by ISCO-68 code 77 (ISCO-88 codes 322–323). Private-sector workers identified by self-employment status. Specialist hospitals generate large increases in total nursing and technical staff (Columns 1–2) but show no significant spillovers to the private sector (Columns 3–4), consistent with the absence of a private-sector wage premium for nurses and allied health workers in Malaysia. Standard errors clustered by district in parentheses.

B.6 Heterogeneous Effects by Hospital Size: Event Study Dynamics

Figure B.3 presents the event study dynamics underlying the size heterogeneity results in Table 5. The physician supply mechanism predicts that crowd-in should concentrate among smaller private hospitals, which require fewer specialists to reach minimum viable scale and are more likely to be founded by individual physicians transitioning from public practice. Panel A shows this prediction: small private hospitals (fewer than 94 beds) show a clear positive trend following specialist public hospital construction, with effects growing steadily over the post-treatment window. Large private hospitals show essentially flat effects, consistent with large urban facilities having access to deeper physician labor markets that are less affected by any single public hospital opening. Panel B shows that non-specialist public hospitals produce weakly negative effects for both size categories, with no evidence of differential crowd-out by hospital size. The absence of size heterogeneity in the non-specialist case is consistent with demand competition operating independently of hospital scale, since a new public hospital draws patients regardless of whether the competing private facility is small or large.

Figure B.3: Effects of Specialist and Non-Specialist Public Hospitals on Small and Large Private Hospitals



Note: This figure presents four pre-period and seven post-period event study estimates from Equation 1. Panel A shows the effects of 14 new specialist public hospitals on the number of small (fewer than 94 beds) and large (94 or more beds) private hospitals within the same district. Panel B shows the effects of 11 non-specialist public hospitals. Each dot represents a point estimate with the corresponding 95 percent confidence interval shown as vertical lines. The reference period is $\ell = -1$. Standard errors are clustered at the district level.

B.7 Sensitivity to Violations of Parallel Trends

The event study design assumes that treated and control districts would have followed parallel trends in private hospital entry absent treatment. I assess sensitivity to violations of this assumption using Rambachan and Roth (2023).

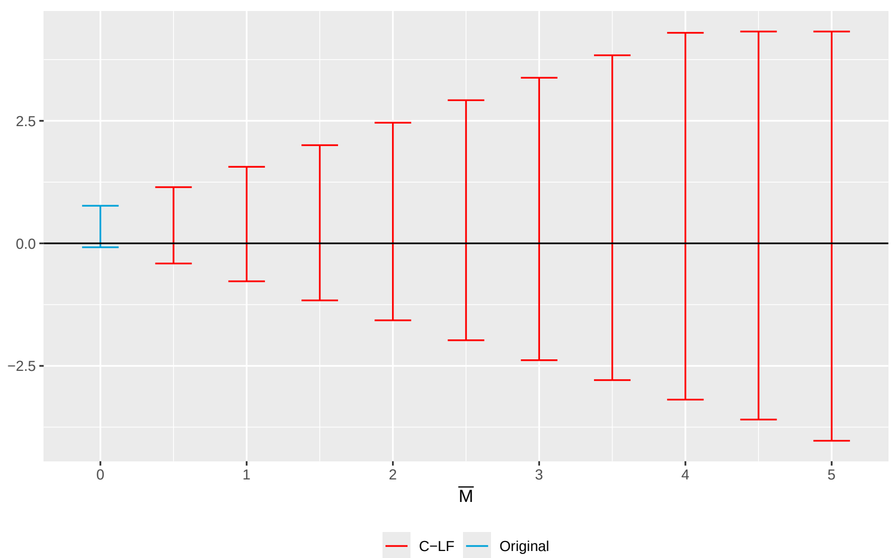
The intuition is straightforward. The pre-treatment event study coefficients are not exactly zero as they fluctuate due to sampling variability and possible minor trend differences. The largest of these pre-treatment fluctuations provides a natural benchmark for how large confounding trends might plausibly be. The test asks: if post-treatment confounding trends were $\bar{M}$ times as large as the worst pre-treatment fluctuation, would the result survive? The breakdown value is the largest $\bar{M}$ at which the answer is yes. An $\bar{M}$ of 1 means the result survives confounding as large as anything visible in the pre-period. An $\bar{M}$ of 2 means it survives confounding twice as large.

Figure B.4 reports the results using $n_{\text{pre}} = 3$ pre-treatment periods ($\ell \in \{-4, -3, -2\}$) and the TWFE variance-covariance structure. For the specialist average post-treatment effect, the robust confidence interval at $\bar{M} = 0.5$ is $[-0.41, 1.15]$. The results are identical using $n_{\text{pre}} = 2$, suggesting that the benchmark is not driven by a single pre-period coefficient. Extending to $n_{\text{pre}} = 4$ includes the binned endpoint ($\ell \leq -5$), which aggregates distant pre-periods into a single coefficient that is 16 times larger in absolute value than any individual pre-period coefficient. this substantially widens the confidence interval (lower bound shifts from -0.41 to -1.32 at $\bar{M} = 0.5$). I report $n_{\text{pre}} = 3$ as the primary specification because the nearby pre-periods provide a more relevant benchmark for post-treatment confounding than distant aggregated event times. The non-specialist result has $\bar{M} \approx 0.5$ for the average effect and $\bar{M} \approx 1.0$ for the first post-period effect.

Two observations provide further context in interpreting these tests. First, the broader evidence in this paper supports parallel trends directly: pre-treatment coefficients are individually small and trend toward zero as the treatment date approaches (Table B.2), the balance table shows no significant differences in education, socioeconomic status, or health facility access (Table B.1), and balancing regressions confirm that predicted private entry is uncorrelated with public hospital construction conditional on district fixed effects (Figure B.5).

Second, the source of the sensitivity is informative. The pre-treatment specialist coefficients are uniformly negative, meaning treated districts were trending toward *fewer* private hospitals relative to controls before treatment. For this pre-trend to confound the positive post-treatment result, the confounding trend would need to reverse sign exactly at the time of treatment. The baseline test allows for this possibility. Imposing instead that the confounding trend does not reverse sign ($\delta_t \leq 0$, using the Δ^{RMNB} restriction), the lower bound of the robust confidence interval tightens from -0.41 to -0.21 at $\bar{M} = 0.5$ and is essentially invariant to $\bar{M}$ thereafter, ranging from -0.26 to -0.20 across $\bar{M} \in [0.5, 5]$. Under this restriction, the remaining uncertainty reflects sampling noise rather than sensitivity to the parallel trends assumption. The low baseline breakdown value is therefore driven by the specific scenario in which a confounding trend flips from negative to positive at treatment, rather than by a continuation of the observed pre-trend pattern.

Figure B.4: Sensitivity of Specialist Hospital Effects to Parallel Trends Violations



Notes: Sensitivity of the average post-treatment effect for specialist public hospitals to violations of the parallel trends assumption, using the relative magnitudes (Δ^{RM}) restriction of Rambachan and Roth (2023) with $n_{\text{pre}} = 3$ pre-treatment periods ($\ell \in \{-4, -3, -2\}$). The horizontal axis shows $\bar{M}$, the maximum ratio of post-treatment trend deviation to the largest pre-treatment deviation. At $\bar{M} = 0$, the confidence interval assumes exact parallel trends. Results are identical using $n_{\text{pre}} = 2$. TWFE variance-covariance structure.

B.8 Heterogeneous Effects by Institutional Context: Pre-1996 Corporatization Era

The crowd-in effects of specialist public hospitals depend on the institutional context in which they operate. During the early 1990s, the Malaysian government pursued corporatization of public hospitals, proposing to maintain government ownership while operating them as profit-maximizing entities. This policy began with incremental reforms including corporatization of Hospital Kuala Lumpur's cardiac unit in 1992 and contracting out of drug distribution systems in 1994. The policy environment reversed with the 7th Malaysia Plan (1996–2000), when the government recommitted to purely public healthcare provision.

Table B.6 presents event study estimates for the pre-1996 period. All types of public hospitals crowded out private entry during this period, including specialist hospitals. The reversal from uniform crowd-out to heterogeneous effects after 1996 suggests that institutional context matters: crowd-in emerges specifically when public hospitals operate as purely public institutions that train specialists who subsequently enter private practice. During the corporatization era, policy uncertainty about the future structure of public hospitals and the possibility that corporatized facilities would retain trained specialists may have weakened the training pipeline that drives the post-1996 crowd-in result.

Table B.6: Effects of Public Hospital Entry on Private Hospitals: Pre-1996 Period

	Number of Private Hospitals		
	(1)	(2)	(3)
All public hospitals	−0.084		
	(0.007)		
Specialist public hospitals		−0.035	
		(0.019)	
Non-specialist public hospitals			−0.095
			(0.009)
Mean Dep. Var.	0.166	0.204	0.181
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N Districts × Year	1,024	592	784
R^2	0.886	0.943	0.900
Events	42	15	27
Estimator	SA	SA	SA

Notes: Each column presents results from separate regressions for the pre-1996 period when public hospitals faced corporatization pressures. The dependent variable is the number of private hospitals in a district. Standard errors clustered at the district level in parentheses.

B.9 Additional Robustness Tables

This subsection collects robustness checks that address specific threats to the main event study estimates.

Sun-Abraham versus TWFE. A concern with two-way fixed effects estimation under staggered treatment timing is that already-treated units can serve as implicit controls for later-treated units, biasing the estimated treatment effect when effects vary across cohorts (Sun and Abraham, 2021). The Sun-Abraham interaction-weighted estimator addresses this by separately estimating cohort-specific effects and aggregating them. If treatment effect heterogeneity across cohorts is minimal, the two estimators should produce similar results. Table B.7 shows this: the SA and TWFE estimates differ by less than 1 percent for specialist hospitals and less than 3 percent for all public hospitals. This suggests that the staggered timing of hospital construction does not introduce meaningful bias.

Balancing Regressions. If public hospitals are systematically built in districts that were already on a trajectory toward more private hospital entry, the event study could confound treatment effects with pre-existing trends correlated with district characteristics. To test this, I first predict the number of private hospitals using the district-level covariates from Table B.1, then estimate Equation 1 with this predicted outcome as the dependent variable. Figure B.5 shows that the correlation between public hospital construction and predicted private entry disappears once district fixed effects are included, indicating that the event study design effectively absorbs the observable confounders.

Excluding Multiple-Treatment Districts. Three districts received more than one public hospital during the study period. If entry of a second public hospital is endogenous to the private hospital response to the first, including these districts could bias the estimates. Table B.8 drops these three districts, reducing the sample from 25 to 22 treatment events. The specialist estimate is somewhat larger in the restricted sample (0.937 versus 0.785), likely reflecting composition as the three excluded districts may have experienced below-average crowd-in. The non-specialist estimate is unchanged (-0.171). Neither change suggests the results are driven by districts with multiple treatments.

Last-Treated as Controls. The main specification uses never-treated districts as the control group. An alternative is to use the last-treated cohort as controls, which ensures that both treatment and control groups eventually receive a public hospital and may therefore be more comparable in terms of unobservable characteristics that predict hospital construction. Table B.9 implements this approach. The specialist estimate of 0.599 is somewhat attenuated relative to the main estimate (0.785) but remains economically large and positive. The non-specialist specification cannot be estimated under this design because both the last-treated control districts and the non-specialist treated districts had zero private hospital entrants.

Comparison Across Staggered DiD Estimators. The recent econometrics literature has proposed several alternative estimators for staggered difference-in-differences designs, each making different assumptions about treatment effect dynamics and the appropriate control group. Table B.10 reports the average post-treatment effect from four estimators: Sun-Abraham, Borusyak-Jaravel-Spiess, Callaway-Sant'Anna, and de Chaisemartin-D'Haultfœuille. All four estimators agree on the qualitative pattern: specialist hospitals crowd in and non-specialist hospitals crowd out. The Callaway-Sant'Anna estimator produces larger point estimates (1.424 for specialist). All four estimators use never-treated districts as controls, so the differences in point estimates reflect differences in how each estimator aggregates cohort-specific effects and handles treatment effect dynamics. Standard errors also vary, reflecting differences in how each accounts for treatment effect heterogeneity and serial correlation.

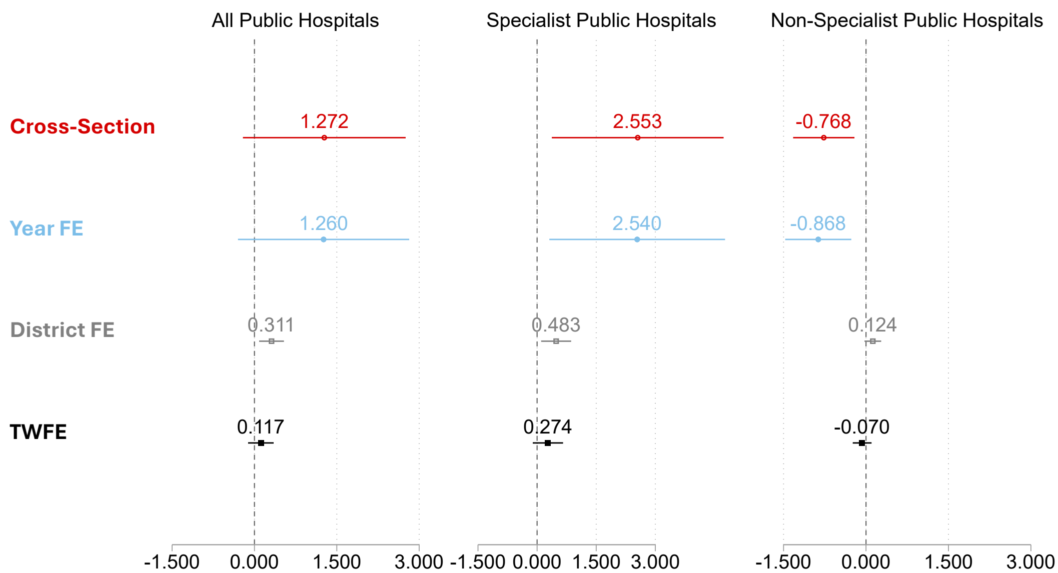
Bed-Size Weighted Effects. If the physician training spillover scales with hospital capacity, larger specialist hospitals should generate proportionally greater crowd-in. Table B.11 tests this by weighting each treatment event by the entering public hospital's bed capacity. The bed-weighted specialist effect (1.069) exceeds the unweighted effect (0.785), consistent with training capacity scaling with hospital size. The non-specialist effect is essentially unchanged under weighting (−0.161 versus −0.171), as expected if crowd-out operates through demand competition rather than a size-dependent mechanism.

Table B.7: Sun-Abraham vs. Two-Way Fixed Effects Estimates

	Number of Private Hospitals		
	All	Specialist	Non-specialist
Panel A. Sun-Abraham			
Post-treatment average	0.465	0.785	−0.171
	(0.094)	(0.108)	(0.009)
Panel B. TWFE with endpoint binning			
Post-treatment average	0.477	0.791	−0.144
	(0.097)	(0.111)	(0.010)
Difference (SA − TWFE)	−0.012	−0.006	−0.027
% difference	2.5%	0.8%	15.8%

Notes: Panel A reproduces the main Sun-Abraham interaction-weighted estimates from Table 1. Panel B reports conventional TWFE estimates with endpoint binning (i.e., binning the earliest and latest relative time indicators to ensure all event times are estimable). The near-identical coefficients for specialist hospitals (less than 1 percent difference) indicate that treatment effect heterogeneity across cohorts is negligible. Standard errors clustered at the district level in parentheses.

Figure B.5: Balancing Regressions



Notes: I first predict the number of private hospitals using district-level characteristics in Table B.1. I then estimate Equation 1 with this predicted outcome as the dependent variable under alternative fixed effects structures. The correlation between public hospital construction and predicted private entry disappears once district fixed effects are included, suggesting that the event study design effectively controls for observable confounders.

Table B.8: Main Effects Robustness: Dropping Multiple Treated Districts

	Number of Private Hospitals		
	(1)	(2)	(3)
All public hospitals	0.457		
	(0.151)		
Specialist public hospitals		0.937	
		(0.114)	
Non-specialist public hospitals			−0.171
			(0.009)
Mean Dep. Var.	1.282	1.709	0.631
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N Districts $\times$ Year	792	594	594
R^2	0.953	0.957	0.930
Events	22	11	11
Estimator	SA	SA	SA

Notes: Excludes three districts that received multiple public hospitals during 1996–2013. Standard errors clustered at the district level in parentheses.

Table B.9: Main Effects Robustness: Last-Treated as Control

	Number of Private Hospitals		
	(1)	(2)	(3)
All public hospitals	0.684		
	(0.081)		
Specialist public hospitals		0.599	
		(0.088)	
Non-specialist public hospitals			—
Mean Dep. Var.	0.979	1.278	—
District Fixed Effects	Yes	Yes	—
Year Fixed Effects	Yes	Yes	—
R^2	0.980	0.975	—
Events	25	14	—
Estimator	SA	SA	—

Notes: Uses last-treated districts as controls. Column (3) cannot be estimated because both last-treated control districts and non-specialist treated districts had zero private hospital entrants. Standard errors clustered at the district level in parentheses.

Table B.10: Post-Treatment Effects on Private Hospital Entry: Comparison of Estimators

	SA	BJSp	CS	DdH
	(1)	(2)	(3)	(4)
All public hospitals	0.465	0.296	1.153	0.289
	(0.094)	(0.267)	(0.323)	(0.177)
Specialist public hospitals	0.785	0.659	1.424	0.558
	(0.108)	(0.292)	(0.336)	(0.191)
Non-specialist public hospitals	-0.171	-0.281	-0.208	-0.119
	(0.009)	(0.236)	(0.181)	(0.110)

Notes: Each column presents post-treatment average effects using different estimators for staggered DiD designs. SA: Sun and Abraham (2021). BJSp: Borusyak et al. (2024). CS: Callaway and Sant'Anna (2021). DdH: de Chaisemartin and D'Haultfœuille (2024). All specifications use never-treated districts as controls. Differences in point estimates reflect variation in how each estimator aggregates cohort-specific effects and handles treatment effect dynamics. Standard errors in parentheses.

Table B.11: Bed-Size Weighted Event Study Estimates

	Unweighted			Bed-Size Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
All public hospitals	0.465			1.013		
	(0.094)			(0.109)		
Specialist		0.785			1.069	
		(0.108)			(0.111)	
Non-specialist			−0.171			−0.161
			(0.009)			(0.014)
Mean Dep. Var.	1.303	1.701	0.631	1.303	1.701	0.631
Pre-Treatment Mean	1.440	2.571	0.000	1.440	2.571	0.000
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N Districts × Year	846	648	594	846	648	594
Events	25	14	11	25	14	11
Estimator	SA	SA	SA	SA	SA	SA

Notes: Columns 1–3 reproduce the main (unweighted) event study results from Table 1. Columns 4–6 weight each treatment event by the entering public hospital's bed capacity. The bed-weighted specialist effect (1.069) exceeds the unweighted effect (0.785), indicating that larger specialist hospitals generate proportionally greater crowd-in, consistent with training capacity scaling with hospital size. The non-specialist effect is essentially unchanged, as expected if crowd-out operates through demand competition rather than a size-dependent mechanism. Standard errors clustered at the district level in parentheses.

B.10 Synthetic Difference-in-Differences

To address concerns about pre-treatment imbalances between treatment and control districts, I re-estimate the main results using the synthetic difference-in-differences estimator (Arkhangelsky et al., 2021). This method constructs synthetic control units that optimally weight both untreated districts and pre-treatment time periods to better match the treated units' characteristics and trends. The specialist SDID estimate (0.692) is positive and similar in magnitude to the main SA estimate (0.785). The non-specialist SDID estimate is attenuated and statistically insignificant, likely reflecting the difficulty of constructing well-matched synthetic controls with only 11 non-specialist treatment events in predominantly rural districts with limited pre-treatment private hospital variation.

Table B.12: Average Treatment Effects on Private Entrants — Synthetic Difference-in-Differences

	Number of Private Hospitals		
	(1)	(2)	(3)
All public hospitals	0.406		
	(0.168)		
Specialist public hospitals		0.692	
		(0.275)	
Non-specialist public hospitals			−0.016
			(0.030)
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Estimator	SDID	SDID	SDID

Notes: Synthetic DiD estimator of Arkhangelsky et al. (2021). Standard errors in parentheses.

B.11 Matching

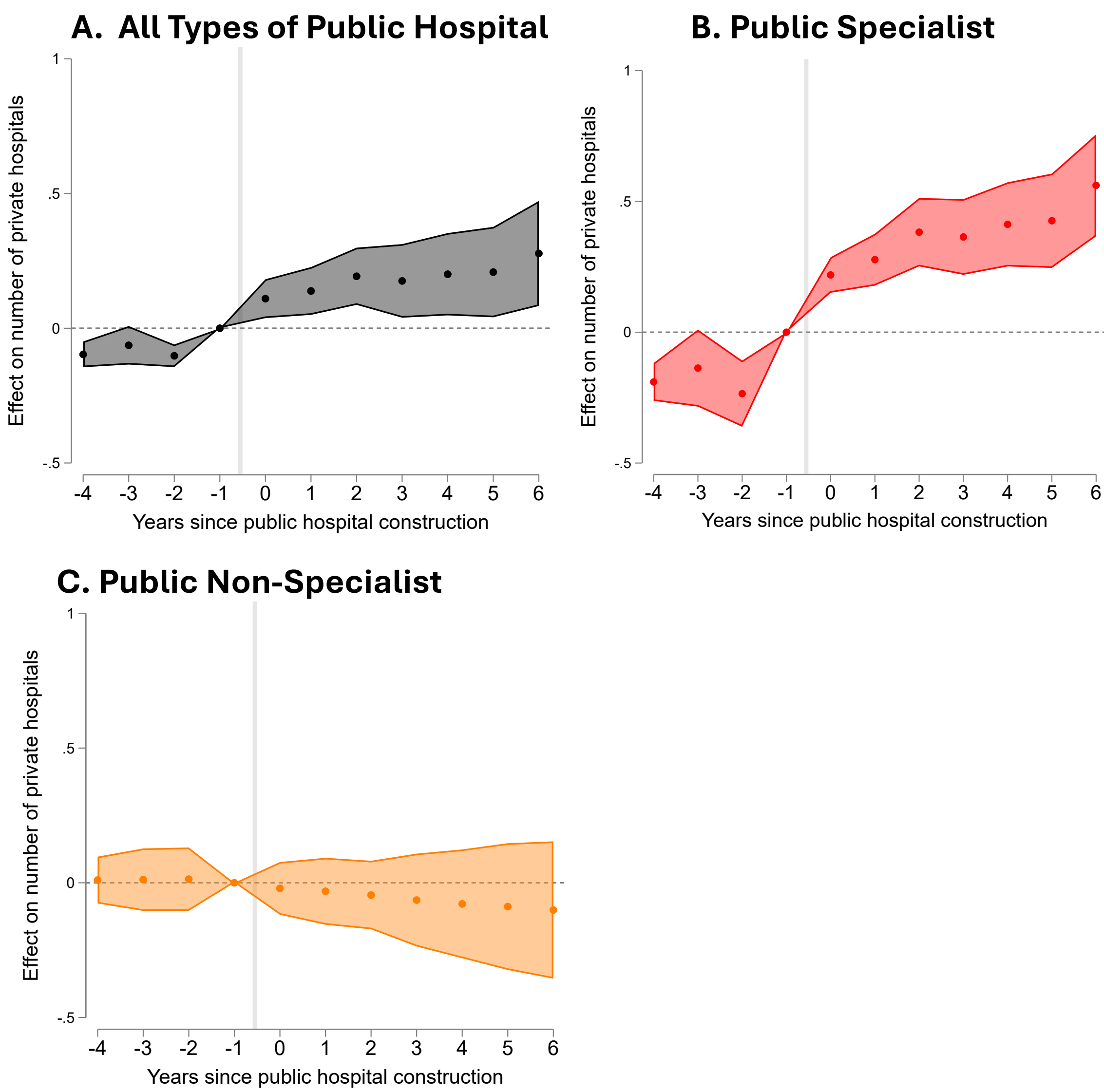
I use coarsened exact matching (CEM) to balance treatment and control districts on rurality and the number of existing public hospitals in 1996 as these two variables show the largest pre-treatment imbalances. The matching procedure reduces the sample from 47 districts (25 treatment, 22 control) to 28 districts (12 treated, 16 control). Table B.13 shows that matching removes all statistically significant differences. Figure B.7 presents the event study for the matched sample, pooling specialist and non-specialist public hospitals. The average post-treatment effect is 0.108 additional private hospitals, representing a 31 percent increase relative to the matched sample's pre-treatment mean. The attenuated magnitude relative to the specialist-only estimate (0.785) is expected, since the matched sample includes non-specialist events that reduce the pooled average.

Table B.13: Post-Matching Summary Statistics by Treatment Status

Variable	Treated (N=12)	Never Treated (N=16)	Difference	P-value
Panel A. Demographics				
Log Population	11.186 (0.870)	11.001 (0.869)	0.185	0.582
Rural Population Share	0.843 (0.224)	0.850 (0.262)	-0.007	0.936
Chinese Share	0.127 (0.116)	0.170 (0.198)	-0.043	0.505
Malay Share	0.402 (0.362)	0.431 (0.384)	-0.029	0.839
Indian Share	0.061 (0.077)	0.039 (0.063)	0.022	0.429
Married Share	0.375 (0.015)	0.398 (0.041)	-0.023	0.078
Financial Services Employment Share	0.005 (0.015)	0.006 (0.011)	-0.001	0.894
Panel B. Education				
College/University Education	0.012 (0.014)	0.014 (0.017)	-0.002	0.772
Secondary Education Completed	0.170 (0.077)	0.205 (0.064)	-0.035	0.200
Primary Education Completed	0.188 (0.048)	0.191 (0.038)	-0.003	0.859
Some Primary Education	0.216 (0.028)	0.209 (0.031)	0.007	0.550
Panel C. Age Distribution				
Age <1	0.031 (0.008)	0.026 (0.008)	0.005	0.106
Age 1–4	0.119 (0.019)	0.110 (0.020)	0.009	0.233
Age 5–18	0.340 (0.039)	0.314 (0.044)	0.026	0.119
Age 19–45	0.369 (0.063)	0.388 (0.062)	-0.019	0.451
Age 46–60	0.095 (0.031)	0.101 (0.031)	-0.006	0.612
Age 61–74	0.034 (0.017)	0.047 (0.020)	-0.013	0.077
Age >74	0.012 (0.009)	0.015 (0.008)	-0.003	0.347
Panel D. Health Facilities				
Number of Private Hospitals	0.094 (0.401)	0.375 (1.500)	-0.281	0.534
Number of Public Hospitals	0.125 (0.345)	0.125 (0.342)	0.000	1.000
Number of Private Doctors	12.500 (36.927)	18.750 (62.915)	-6.250	0.762
Distance to Nearest Public Hospital (km)	33.054 (13.585)	36.570 (40.181)	-3.516	0.774
Distance to Nearest Private Hospital (km)	118.454 (88.809)	113.839 (122.953)	4.615	0.913

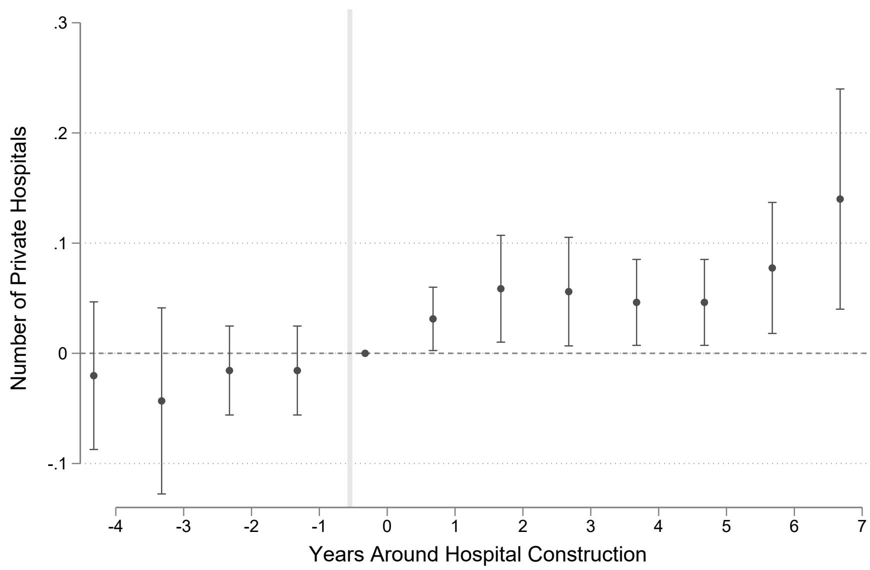
Notes: Standard deviations in parentheses. Difference = Treated - Never Treated. P-values from two-sample t-tests. Sample reduced from 47 districts to 28 districts (12 treated, 16 control) after coarsened exact matching on rurality and number of existing public hospitals.

Figure B.6: Synthetic Difference-in-Differences: Dynamic Treatment Effects



Note: Panel A: all public hospitals. Panel B: specialist public hospitals. Panel C: non-specialist public hospitals. Control units selected using the Synthetic DiD procedure. Shaded area represents the 95 percent confidence interval.

Figure B.7: Event Study of Matching on Private Hospital Entrants



Note: Event study estimates using the Sun and Abraham (2021) estimator on the coarsened exact matched sample (12 treated, 16 control districts). Combines both specialist and non-specialist public hospitals. Matching variables: rurality and number of existing public hospitals in 1996. The average post-treatment effect is 0.108. Standard errors clustered at the district level.

C Further Details on Model and Estimation

C.1 Demand Estimation Details

I specify a discrete choice model of hospital choice for birth deliveries in Malaysia using Berry et al. (1995, 2004) and estimate the model using the PyBLP Python package (Conlon and Gortmaker, 2020, 2023). The model incorporates both aggregate market share data and micro moments from a national survey of potential mothers to identify demand parameters and calculate expected profits from entering specific districts.

I model $d = 1, 2, \ldots, \mathcal{D} = 95$ district-level markets where child-seeking women choose among available public and private hospitals, alongside private maternity centers for birth deliveries. In each market t, I define the choice set to include $j = 1, 2, \ldots, J_t^{pub}$ public hospitals priced at MYR 100 per delivery, $j = J_t^{pub} + 1, \ldots, J_t$ private hospitals with profit-maximizing prices, an average private maternity option if a district has a private maternity center, and $j = 0$ representing the outside option of traditional or home births. Each public hospital is operated by the government at an exogenously fixed price. Each private hospital j is operated by firm f, which may be a hospital chain (KPJ, Pantai, Columbia Asia, Sime Darby) or an independent entrepreneur. I specify the indirect utility of child-seeking woman i in district d from choosing j following the standard BLP specification:

$$U_{ijd} = \delta_{jd} + \mu_{ijd} + \epsilon_{ijd}$$

I define the mean utility as $\delta_{jd} = \alpha p_{jd} + X_{1jd}\beta + \xi_{jd}$, where p_{jd} represents the price per delivery in thousands of MYR, X_{1jd} contains standardized hospital characteristics including congestion (bed occupancy rate), staff, number of specialties, and hospital type indicators, $\alpha < 0$ captures the base price sensitivity, β represents parameters on hospital characteristics, and ξ_{jd} denotes unobserved hospital quality.

I model individual heterogeneity in price sensitivity through the random coefficients specification $\mu_{ijd} = X_{2jd}(\Sigma\nu'_{id} + \Pi a'_{id})$, where X_{2jd} represents a subset of X_{1jd} including a constant, price, and private hospital indicator. The agent demographic variables a_{id} capture district-level characteristics including low income, mid income, high income shares, distance to nearest hospital, private insurance coverage, and chronic disease prevalence. I assume unobserved individual heterogeneity ν_{id} follows a standard normal distribution, Σ represents a 3×3 Cholesky matrix governing unobserved taste heterogeneity, and Π forms a 3×7 matrix measuring how preferences vary with observable demographics. Importantly, price sensitivity varies across income groups through the Π matrix, allowing low-income consumers to respond more strongly to price changes than high-income consumers even though hospitals charge the same price to all consumers.

Related to the utility specification in Equation 3, the components of the main text utility map to the BLP structure as follows: the mean utility δ_{jd} incorporates the hospital characteristics $H_j\beta$ from Equation 3 along with the base price effect αp_j. The individual heterogeneity term μ_{ijd} captures the income group-specific price sensitivity deviations through Π, the travel disutility $\lambda_i \text{distance}_{ij}$, and the private hospital interactions with individual attributes $\text{private}_j(Z_i)$ from the main specification. The random error term ε_{ij} corresponds directly to ε_{ijd} in this appendix. This decomposition allows me to separate hospital-level mean preference from individual-specific taste variations.

For a given draw of individual heterogeneity, the conditional choice probability follows the logit form $s_{ijd}(\nu_i, a_i) = \frac{\exp(\delta_{jd}+\mu_{ijd})}{1+\sum_{k\in J_d}\exp(\delta_{kd}+\mu_{ikd})}$. Aggregate market shares are computed by integrating over the distribution of heterogeneity: $s_{jd} = \int s_{ijd}\, dF(\nu_{id}, a_{id})$. On the supply side, I assume private hospital set prices while treating public hospital pricing as exogenously determined. Private hospital f in market d chooses a single price p_{jd} for each of its hospitals $j \in J_{fd}$ to maximize profits:

$$\pi_{fd} = \sum_{j\in J_{fd}} (p_{jd} - c_{jd}) \cdot s_{jd}(p) \cdot M_d$$

where M_d represents the total number of births in district d, $s_{jd}(p)$ is the aggregate market share (integrating over consumers with heterogeneous price sensitivities), and c_{jd} is the marginal cost. The multi-product Bertrand pricing first-order conditions yield the standard markup equation $p_{jd} - c_{jd} = \eta_{jd} = -[\Delta^{-1}s]_{jd}$, where Δ represents the Jacobian matrix of demand derivatives $\frac{\partial s_k}{\partial p_j}$ across products and $\mathscr{H}$ denotes the ownership matrix with $\mathscr{H}_{jk} = 1$ if hospitals j and k are owned by the same firm.

Rather than imposing a parametric cost function, I recover marginal costs directly from the first-order conditions using $c_{jd} = p_{jd} - \eta_{jd}$. The recovered marginal costs represent the marginal cost of providing an additional birth delivery at each private hospital (which is distinct from the fixed cost or operational costs of entry).

To identify the demand parameters, particularly the distribution of random coefficients, I incorporate micro moments from a national survey of potential mothers. I specify these moments as $\bar{g}_{M,m} = f_m(\bar{v}) - f_m(v)$, matching observed versus simulated conditional demographic expectations. Specifically, I include moments for the expected probability that private hospital users belong to different income categories, their average distance to hospitals, insurance coverage rates, and chronic disease prevalence.

I estimate the model by GMM, minimizing the objective function $\min_\theta q(\theta) = \bar{g}(\theta)' W \bar{g}(\theta)$, where θ includes the non-concentrated parameters Σ and Π, and $\bar{g}(\theta)$ contains both demand-side moments $\bar{g}_D = \frac{1}{N}\sum_{j,d} Z'_{D,jd}\xi_{jd}$ and the micro moments $\bar{g}_M$ described above. My identification relies on differentiation instruments following Gandhi and Houde (2019), which measure local competition based on other hospitals' characteristics within each district, combined with the micro moments that help pin down the distribution of random coefficients.

C.1.1 Demand Estimation Sample Construction

In 2013, there were a total of 135 private hospitals alongside 70 maternity centers, and 135 public hospitals. To construct the demand estimation data, I first drop hospitals that do not provide obstetrics services, resulting in 122 private hospitals. Next, I drop private hospitals that did not have a maternity package during my primary data collection in 2013, resulting in 105 private hospitals.

Among these hospitals, 24 private hospitals and 12 public hospitals did not report birth deliveries in the inpatient admissions database, though they do report total inpatient admissions in 2013. For these hospitals, I assume that birth deliveries comprise 10.6 percent of total inpatient admissions for public hospitals and 5.9 percent for private hospitals, based on the mean proportion of deliveries observed among reporting hospitals (See Table C.6,

Table C.5 and Figure C.6 for related distribution). I drop 18 private hospitals that did not report total inpatient admissions or birth deliveries in the electronic health records.

My final estimation sample includes 87 private hospitals out of an initial 135, after excluding facilities with missing survey agent data, zero reported prices, missing total inpatient admissions, or no obstetrics services. My final dataset includes 87 private hospitals, 19 districts with private maternity centers, 57 non-specialist public hospitals and 55 specialist public hospitals. I obtain the outside option share from the national survey of families' preferences on seeking home or traditional births. To ensure that these data limitations do not bias my results, I provide a parsimonious version of my demand estimates by dropping hospitals that have missing prices or missing inpatient admissions, showing that the random coefficients logit model is comparable (see Table C.2 compared to Table C.4).

C.1.2 Demand Results

I tabulate the demand estimates in Table C.2 and the fitted micro moments in Table C.3. The results show strong income-based private preferences in the market. Only 7.9 percent of low-income individuals use private hospitals, compared to 24.0 percent for mid-income and 68.1 percent for high-income consumers. Price sensitivity exhibits strong income-based heterogeneity. Low-income consumers show the strongest price sensitivity (base effect of -1.79 plus interaction of -1.71, totaling -3.50), followed by mid-income consumers (total of -2.86), while high-income consumers are the least price sensitive (total of -1.80).

The congestion coefficient (0.363) with its negative squared term (-0.150) suggests consumers prefer moderately busy hospitals, likely viewing some congestion as a signal of quality while avoiding overly crowded facilities. Consumers show strong preferences for hospitals with more specialties (0.494), while the staff coefficient (-0.189) suggests that raw staff count is not a key quality indicator for consumers.

The large positive coefficient on private hospital usage among insured individuals (3.10) indicates that insurance coverage, despite not covering maternity care directly, strongly predicts private hospital choice. This likely reflects choice inertia among families who are regular private healthcare users. The negative coefficient on chronic conditions (-1.38) suggests that women with chronic conditions may prefer public hospitals, possibly due to better coordination with existing public sector care or cost considerations.

Distance effects are captured through the interaction term (-0.492), showing that consumers' willingness to travel for hospitals varies, though the effect is not statistically significant in this specification. One important observation is that the coefficient for distance is negative, but imprecisely estimated. This is likely due to the stated preference nature of the survey design, where respondents may underweight distance considerations when reporting hypothetical choices.

C.2 Expected Entry Profits: Construction and Benchmarking

As described in the main text, I recover hospital-specific marginal costs and profits from Bertrand-Nash first-order conditions using the demand estimates from Column (4) of Table C.2. Ownership groups include hospital chains (KPJ, Pantai, Columbia Asia, Sime Darby), solo entrepreneurship groups, and the government. The distribution of recovered profits and markups are in Figure C.10.

C.2.1 Temporal Alignment

To construct expected entry profits for the dynamic model beginning in 1996, I face a temporal alignment challenge. The demand system is estimated using 2013 data, but I need profit expectations relevant to 1996 entry decisions. Given data constraints as I only observe detailed price and admission data for 2013, I proceed in three steps. First, I use the estimated demand elasticities to recover hospital-level margins and compute birth-delivery profits, then scale to total hospital profits using each hospital's ratio of birth deliveries to total admissions (which varies from 0.06 to 0.65 across facilities; see Figure C.6). Second, I deflate 2013 prices and costs to 1996 MYR using the national consumer price index. Third, I restrict the hospital set to facilities operating by 1996 and aggregate to the district level. I maintain 2013 birth volumes rather than backcasting to 1996 levels. Total live births in Malaysia were roughly stable between 1996 and 2013 (approximately 550,000 versus 510,000), as declining fertility rates largely offset population growth. The key variation for identification comes from cross-district differences in market structure rather than temporal trends in birth volumes.

I construct expected entry profits $\mathbb{E}[\pi_d]$ at the district level as the share-weighted mean of incumbent profits:

$$\mathbb{E}[\pi_d] \equiv \frac{\sum_{j \in \mathcal{I}_d} s_j \, \pi_j}{\sum_{j \in \mathcal{I}_d} s_j},$$

where $\mathcal{I}_d$ denotes the set of private hospitals operating in district d by 1996, s_j are BLP demand shares, and π_j are hospital-level profits deflated to 1996 MYR. For districts without 1996 private incumbents, I apply national-average entrant characteristics (market share, profit margin, births-to-admissions ratio) scaled to the district's birth volume to estimate expected profits.

C.2.2 Sensitivity to Profit Assumptions

The share-weighted approach relies on a strong assumption about how the private profit pool evolves with entry. In reality, the private profit pool can increase or decrease depending on competitive responses. If private firms improve quality or services to attract patients away from public hospitals, the private profit pool may increase beyond what the static profits predict. Conversely, if incumbent private hospitals respond to entry by reducing prices to maintain market share, or if public hospitals improve their quality in response to increased private competition, the private profit pool may decrease. Additionally, further entrants could intensify price competition and reduce the total profits available to private hospitals.

To test the sensitivity of entry cost estimates to this assumption, I allow market-level profits to vary above or below the baseline through a scaling parameter λ. Expected entrant profit is then $\mathbb{E}[\pi_d] \cdot (1 + \lambda)$, where $\lambda \in \{-0.10, 0.00, 0.10\}$ captures scenarios where total market profits contract by 10 percent, remain unchanged, or expand by 10 percent relative to the baseline. For districts with no 1996 private incumbents, I construct a national-average synthetic entrant using private-hospital national averages of market share, profit margins, and the births-to-admissions ratio applied to the district's birth market size. Results under all three scenarios are reported in Table 6 of the main text.

C.2.3 External Benchmarking

To assess the external validity of the hospital profit estimates, I benchmark them against publicly available annual reports of major hospital groups. For this comparison, I use the un-deflated 2013 estimates (in nominal MYR) rather than the 1996-deflated values used in the structural model. KPJ Healthcare operated approximately 22 hospitals in 2013. Their annual reports indicate average profit per hospital of approximately RM 2.3 million in 2005 (with 15 hospitals) and RM 5.8 million by 2015 (with approximately 25 hospitals). For IHH Holdings (the parent company of Pantai Hospitals), their 2015 annual report suggests a profit of roughly RM 16 million per hospital. My 2013 estimates for KPJ-owned hospitals (RM 8.0 million) and Pantai hospitals (RM 13.7 million) fall within the plausible range implied by these benchmarks, though differences in reporting periods, accounting definitions, and the fact that my estimates are derived from a single service line (scaled to total admissions) limit direct comparability.

Figure C.1 maps expected annual entrant profits (in thousands of 1996 MYR) under the baseline $\lambda = 0$ scenario. Profits concentrate in urban districts with larger populations, but substantial cross-district variation remains, from near zero in rural districts to over 6 million MYR in the most profitable urban markets. The mean annual profits for an 'average' private hospital in 1996 is approximately 639 thousand MYR, with a standard deviation of 890 thousand MYR. This significant variation in expected profits across districts is important for identifying entry costs in the dynamic model, as hospitals weigh these profits against entry costs when making their entry decisions.

C.3 First-Stage CCP and Transition Estimates

C.3.1 CCP of Private Entry

Table C.1 reports the logit for the conditional choice probability of private entry, estimated on the state vector $(n_{dt}^{\text{priv}}, n_{dt}^{\text{pubS}}, n_{dt}^{\text{pubNS}}, \log \text{pop}_{dt}, \text{doc\_bin}_{dt})$. Doctor stock enters flexibly via quintile dummies (bin $= 0$ for zero doctors, bins 1–4 for physician stock quintiles). Standard errors are clustered at the district level.

C.4 Model Validation

I validate the model by predicting the spatial distribution of private hospitals. Starting from the observed 1996 initial conditions, I simulate entry decisions forward for 16 years using the estimated model. In each simulation, both the entrant and other private competitors make sequential entry decisions based on evolving market states. Physicians, population, and public hospital stocks all update according to estimated transition functions. I average across 500 simulations per district to obtain predicted private hospital counts for 2012, which I compare to actual counts from the panel data.

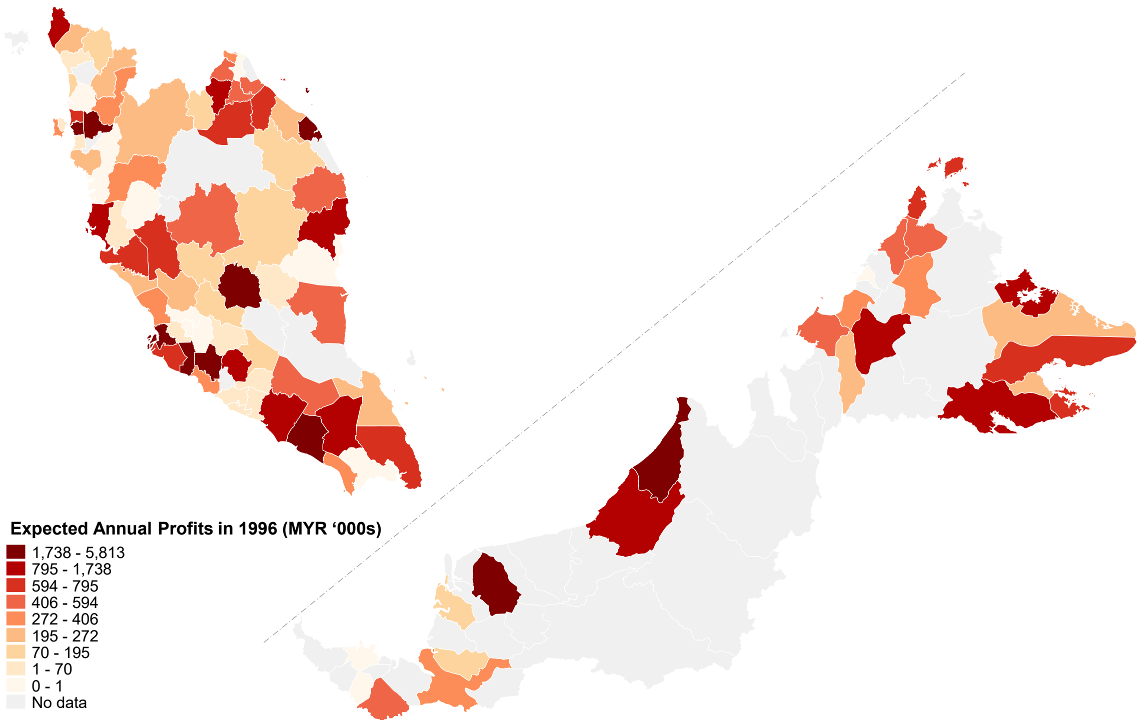
Figure C.11 shows the model achieves strong predictive power, with a correlation of 0.947 between predicted and actual hospital counts and a root mean squared error of 1.25 hospitals. Most districts cluster tightly around the 45-degree line, showing that the model accurately captures both the intensive margin (how many hospitals enter high-activity districts) and the extensive margin (which districts remain without private hospitals).

Table C.1: CCP of Private Entry (Logit and Marginal Effects, District-clustered SEs)

	Logit Coefficients		Marginal Effects (dy/dx)	
	Estimate	Std. Error	Estimate	Std. Error
Doctor-stock quintiles (baseline = 0 Doctors)				
Q1	0.704	0.524	0.021	0.015
Q2	0.707	0.500	0.021	0.014
Q3	0.497	0.565	0.014	0.017
Q4	0.936	0.568	0.031	0.018
n^{pubS}	−0.306	0.118	−0.010	0.004
n^{pubNS}	−0.690	0.200	−0.023	0.008
n^{priv}	−0.111	0.029	−0.004	0.001
log(Population)	2.335	0.306	0.078	0.012
Constant	−32.460	3.778		
Observations		1,615		
District clusters		95		
Pseudo R^2		0.314		

Notes: Dependent variable is an indicator for private entry in district d and year t. Regressors include doctor-stock quintile dummies (Q1–Q4, baseline = 0 doctors), counts of public specialist and non-specialist hospitals, incumbent private hospitals, and log population. Marginal effects are average partial effects on Pr(Entry). Standard errors are clustered by district.

Figure C.1: Expected Profits from Entering a District in 1996



Notes: Expected profits $\mathbb{E}[\pi_d]$ computed at district level under baseline scenario ($\lambda = 0$). Hospital-level profits estimated from BLP demand, scaled from birth-delivery to total hospital profits using facility-specific ratios, and deflated to 1996 MYR. For districts with 1996 private incumbents, expected entrant profit equals share-weighted mean of incumbent profits using BLP shares as weights. For districts without 1996 incumbents, a synthetic private hospital entrant is assumed with national-average characteristics. Birth volumes maintained at 2013 levels. Public hospital prices fixed at MYR 100.

The model performs well across most of the distribution but slightly underpredicts entry in the highest-entry districts (those with more than 15 hospitals). These are Kuala Lumpur and Petaling Jaya, the largest metropolitan districts where hospitals benefit from agglomeration effects not fully captured by the parsimonious state specification. Despite this limitation, the strong predictive power provides confidence that the structural estimates capture the economic primitives driving hospital entry decisions.

C.5 Observational Equivalence of Entry Cost and Marginal Cost Channels

A natural concern is that physician supply may affect not only one-time entry costs (through initial recruitment) but also ongoing marginal costs (through labor market thickness). This appendix shows that the two channels are observationally equivalent for entry decisions, characterizes what the estimated entry cost parameter γ_3 identifies, and bounds the portion attributable to capitalized marginal cost savings.

C.5.1 Setup

Consider two models of how physician supply docs_{dt} affects private hospital profitability.

Model A (Estimated Model): Physicians affect only entry costs.

$$\bar{C}^A_{dt} = \gamma^A_0 + \gamma_1 \ln(\text{pop}_{dt}) + \gamma_2 \ln(\text{LandPrice}_d) + \gamma^A_3 \cdot \text{docs}_{dt} + \delta_t \tag{13}$$
$$\pi^A_{dt} = \pi(\mathbf{p}, \mathbf{c}; S_{dt}) \tag{14}$$

where marginal costs $\mathbf{c}$ are recovered from Bertrand first-order conditions and do not depend on docs_{dt}. Probabilistic entry is generated by i.i.d. Type I Extreme Value action-specific shocks as in equation (7).

Model B (Alternative Model): Physicians affect both entry costs and marginal costs.

$$\bar{C}^B_{dt} = \gamma^B_0 + \gamma_1 \ln(\text{pop}_{dt}) + \gamma_2 \ln(\text{LandPrice}_d) + \gamma^B_3 \cdot \text{docs}_{dt} + \delta_t \tag{15}$$
$$c^B_j(\text{docs}_{dt}) = \bar{c}_j - \eta \cdot \text{docs}_{dt} \tag{16}$$
$$\pi^B_{dt} = \pi(\mathbf{p}^B, \mathbf{c}^B(\text{docs}_{dt}); S_{dt}) \tag{17}$$

where $\eta > 0$ captures how a thicker physician labor market reduces marginal costs.

C.5.2 Observational Equivalence

Under both models, the BBL procedure computes revealed entry costs from the Hotz-Miller inversion: $\kappa_{dt} = \Delta W_{dt} - \eta_{dt}$, where $\Delta W_{dt} = \Pi(S_{dt}) - V^{\text{wait}}(S_{dt})$ is the simulated value gap (with Π denoting the discounted profit stream from immediate entry) and $\eta_{dt} = \ln(P(\text{enter})/P(\text{wait}))$ is the log-odds from observed entry decisions. Critically, η_{dt} is computed from data and is model-invariant—both models rationalize the same observed entry probabilities.

Proposition C.1 (Observational Equivalence)**.** *If the researcher estimates Model A but Model B is the true data-generating process, the estimated entry cost parameter satisfies:*

$$\gamma^A_3 = \underbrace{\gamma^B_3}_{\substack{\textit{Pure entry}\\ \textit{cost effect}}} - \underbrace{\frac{\partial}{\partial docs_{dt}} \left[\Delta W^B_{dt} - \Delta W^A_{dt}\right]}_{\substack{\textit{Capitalized marginal}\\ \textit{cost savings}}} \tag{18}$$

The second term is positive, so γ^A_3 is more negative than the true entry cost effect γ^B_3. Intuitively, Model A attributes to entry costs not only the true recruitment cost savings but also the capitalized value of lower ongoing labor costs that the entrant enjoys after entry.

Proof. Under Model B (the true DGP), the correctly specified revealed cost satisfies $\kappa^B_{dt} = \Delta W^B_{dt} - \eta_{dt} = \bar{C}^B_{dt}$. Under Model A (the estimated model), the researcher computes $\kappa^A_{dt} =$

$\Delta W^A_{dt} - \eta_{dt}$. Since η_{dt} is model-invariant:

$$\kappa^A_{dt} = \kappa^B_{dt} - \left(\Delta W^B_{dt} - \Delta W^A_{dt}\right) = \bar{C}^B_{dt} - \underbrace{\left(\Delta W^B_{dt} - \Delta W^A_{dt}\right)}_{\substack{\text{Additional value of} \\ \text{entering now under Model B}}} \tag{19}$$

The term $\Delta W^B - \Delta W^A$ is positive because entering immediately is relatively more valuable under Model B: the entrant earns higher profits (due to lower marginal costs) for the full remaining horizon, whereas under the "wait" policy, these savings accrue only from the stochastic future entry date onward. The difference is the value of the marginal cost savings during the delay period between "enter now" and eventual entry under the wait policy. Taking derivatives with respect to docs_{dt} on both sides yields the result. □

Corollary C.2 (Upper Bound on Capitalized Savings)**.** *Under the assumption that physician supply follows an AR(1) process with persistence ρ and the marginal cost effect η is constant, the capitalized savings term is bounded above by:*

$$\underbrace{\frac{\partial}{\partial docs_{dt}}\left[\Delta W^B_{dt} - \Delta W^A_{dt}\right]}_{\substack{\textit{Capitalized MC savings} \\ \textit{absorbed into } \gamma^A_3}} \leq \underbrace{\frac{\eta \cdot \bar{s} \cdot M_d}{1 - \beta\rho}}_{\substack{\textit{Present value of} \\ \textit{MC savings per doctor} \\ \textit{if entry is delayed forever}}} \tag{20}$$

where η is the marginal cost reduction per doctor (MYR per delivery per doctor), $\bar{s}$ is the entrant's average market share, and M_d is the total number of births in district d. The bound is achieved in the limiting case where the "wait" policy delays entry indefinitely. In practice, because the CCP policy eventually leads to entry, the actual capitalized savings absorbed into γ^A_3 are strictly smaller than this upper bound.

Proof. Under "enter now," the entrant earns the marginal cost savings $\eta \cdot \text{docs}_{d,t+\tau} \cdot \bar{s} \cdot M_d$ for every period $\tau = 0, \ldots, T - t$. Under the "wait" policy, entry occurs at a stochastic future time $\tau^* > 0$, so the savings accrue only from τ^* onward. The value gap difference is therefore:

$$\frac{\partial(\Delta W^B - \Delta W^A)}{\partial \text{docs}_{dt}} = \eta \cdot \bar{s} \cdot M_d \cdot \sum_{\tau=0}^{T-t} \beta^\tau \rho^\tau \cdot \Pr(\text{not yet entered by } \tau) \tag{21}$$

Since $\Pr(\text{not yet entered by } \tau) \leq 1$ for all τ, the expression is bounded above by $\sum_{\tau=0}^{T-t} \beta^\tau \rho^\tau \cdot \eta \cdot \bar{s} \cdot M_d \approx \frac{\eta \cdot \bar{s} \cdot M_d}{1-\beta\rho}$ for large T. □

C.5.3 Interpretation

The Proposition establishes that γ^A_3 captures the *total* effect of physician supply on the net incentive to enter, combining two components: the pure entry cost reduction (γ^B_3) and the capitalized value of ongoing marginal cost savings. The Corollary bounds the second component.

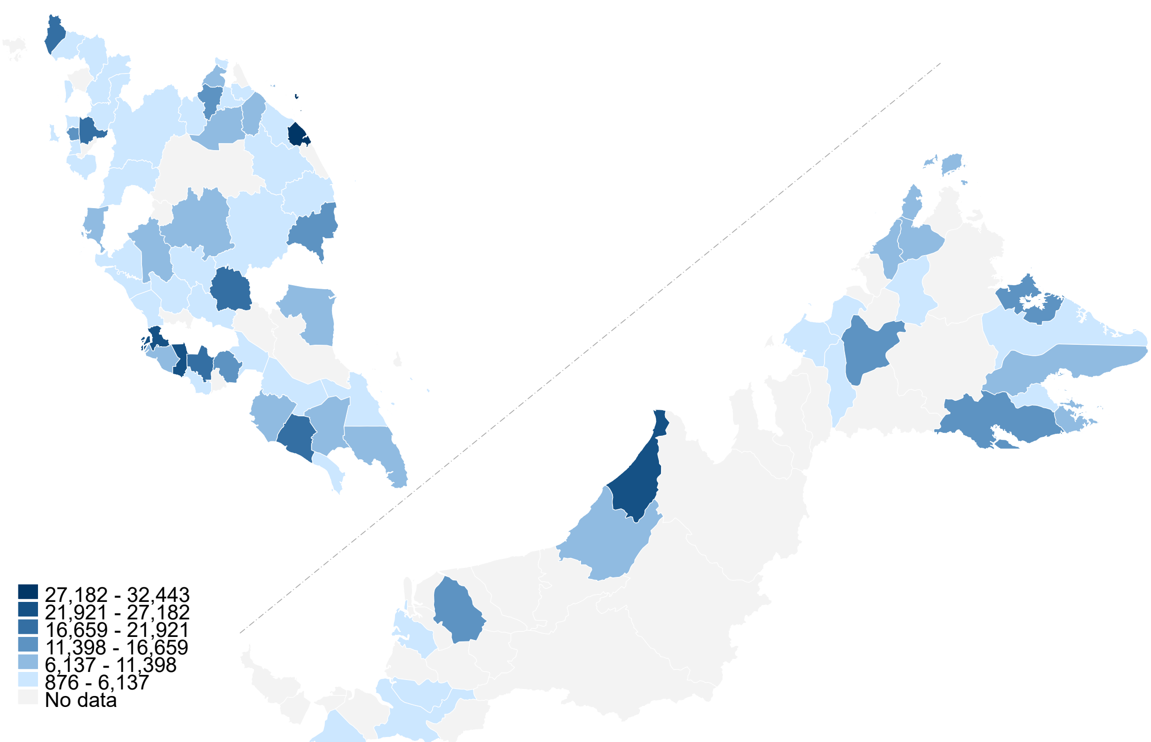
To interpret the bound concretely: for the median district in the sample ($M_d \approx 5{,}000$ births, $\bar{s} \approx 0.03$), the bound equals $\frac{\eta \times 0.03 \times 5{,}000}{1-0.95 \times 0.749} \approx 507\eta$. If each additional doctor reduces the marginal cost of a delivery by MYR 1 ($\eta = 0.001$ thousand MYR), the bound on capitalized savings is approximately MYR 0.5 thousand per doctor, which is small relative to the estimated $\hat{\gamma}_3 \approx -28$ thousand MYR per doctor. Even at $\eta = 0.01$ (MYR 10 per delivery per doctor), the capitalized savings account for at most MYR 5 thousand per doctor, or roughly 18 percent of the total estimate. The pure entry cost channel therefore accounts for the majority of γ_3^A under plausible values of η.

More importantly, both channels operate in the same direction: physician supply reduces entry barriers whether through cheaper initial recruitment or through lower ongoing labor costs. For understanding why specialist hospitals generate crowd-in, the distinction is immaterial. The 26 percent cost reduction reported in the main text should be interpreted as the total effect of physician supply on the attractiveness of entry, which is the economically relevant quantity for explaining the reduced-form crowd-in finding.

Separating the two channels would require either within-hospital variation in labor costs as local physician supply changes, direct data on hospital-level input prices, or structural assumptions on the hospital production function—none of which are available in this setting.

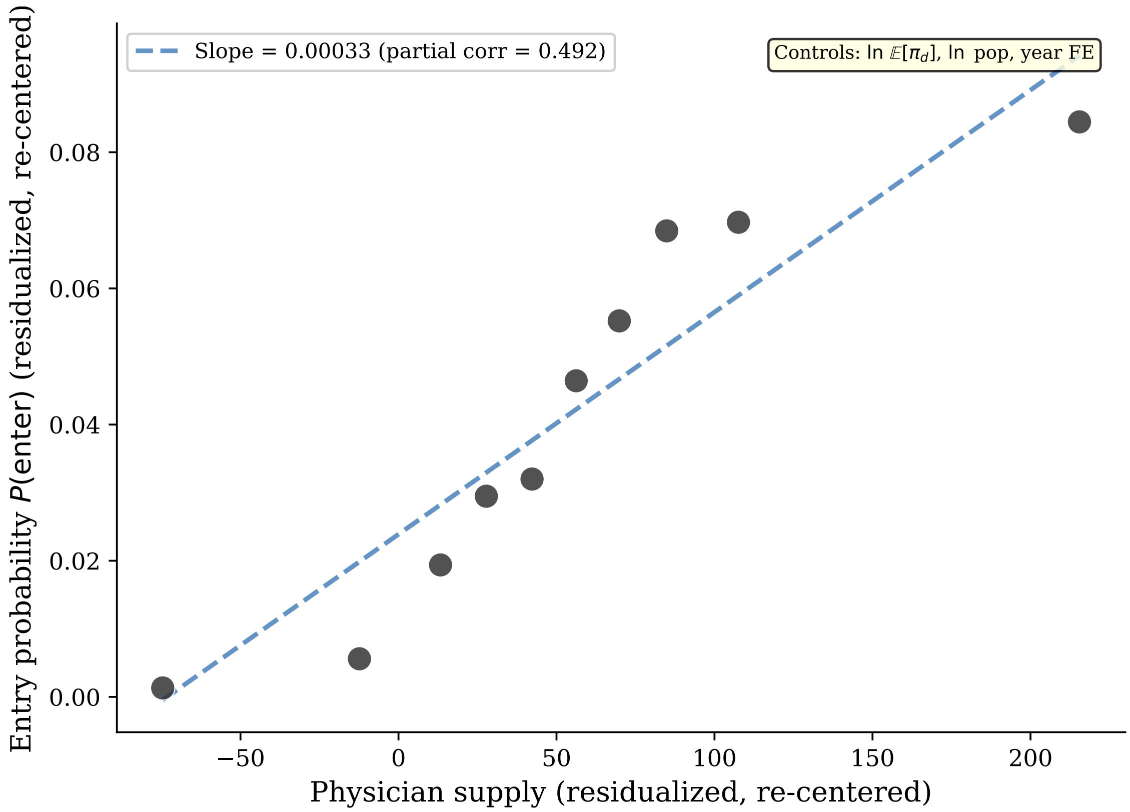
C.6 Additional Tables and Figures

Figure C.2: Spatial Distribution of Revealed Entry Costs, 1996



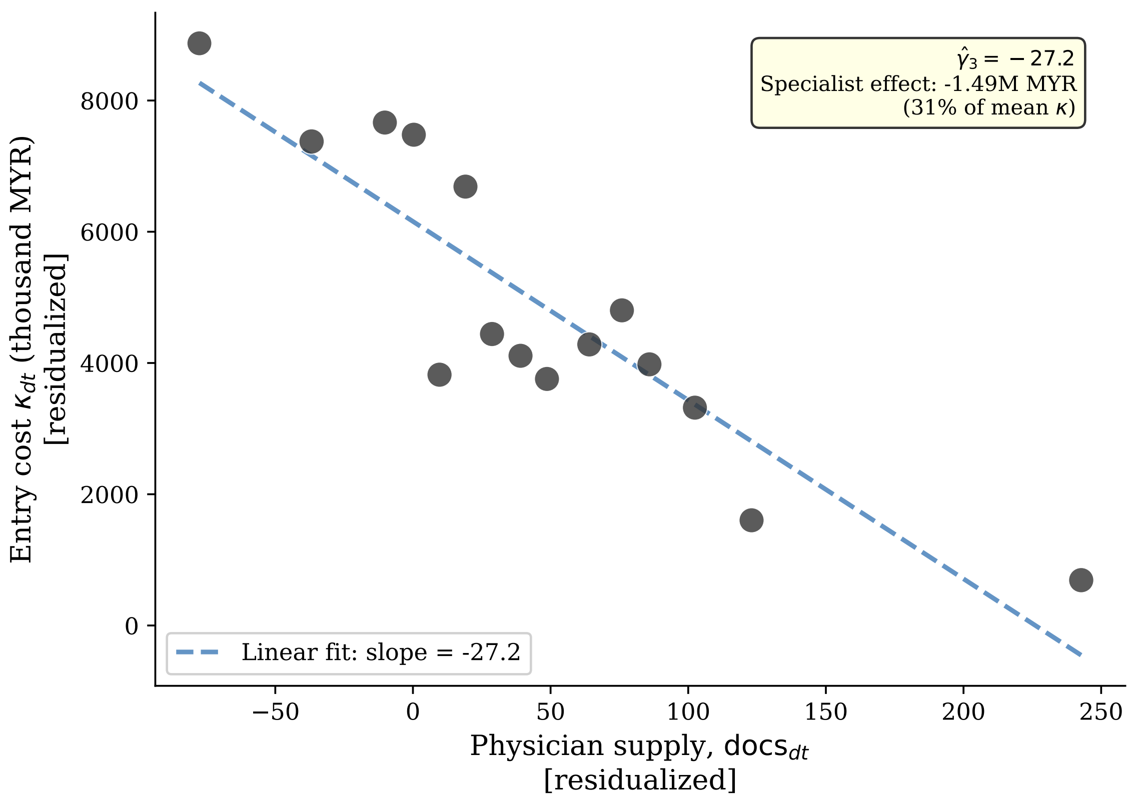
Notes: Each point represents a district's estimated entry cost κ_{dt} in 1996 under the baseline profit scenario ($\lambda = 0$). Mean entry cost is RM 5.09 million; mean annual profit is RM 639 thousand, implying that on average a private hospital would need to operate for approximately 8.7 years to recoup entry costs. High entry costs concentrate in rural districts lacking physicians and public hospitals.

Figure C.3: Structural Identification: Entry Probability and Physician Supply



Notes: Residualized binscatter of private entry probability $P(\text{enter})$ on physician supply docs_{dt}, after partialing out $\ln \mathbb{E}[\pi_d]$, $\ln(\text{pop}_{dt})$, and year fixed effects from both variables. Each point is the mean of a quantile bin. The upward slope (partial correlation = 0.49) shows that conditional on expected profit levels and market size, districts with greater physician supply are substantially more likely to attract private entry. This is the identifying variation for the structural parameter γ_3: the model interprets this residual relationship as evidence that physician supply lowers entry costs. The identification comes primarily from within-district variation over time as specialist hospitals open and train physicians; the 1996 cross-section yields a near-zero partial correlation (-0.003). $N = 1{,}598$ district-year observations, 94 districts, 1996–2012. Axes re-centered at unconditional means for interpretability.

Figure C.4: Revealed Entry Costs and Physician Supply



Notes: Residualized binscatter of revealed entry costs κ_{dt} on physician supply docs_{dt}, after partialing out $\ln(\text{pop}_{dt})$, $\ln(\text{LandPrice}_d)$, and year fixed effects from both variables. The slope (-27.2) corresponds to the second-stage OLS estimate $\hat{\gamma}_3$: each additional physician reduces entry costs by approximately RM 27 thousand. One specialist public hospital (increasing physician supply by 54.7) implies a cost reduction of RM 1.49 million, or 31 percent of mean entry costs. $N = 1{,}566$ district-year observations after trimming the 1st and 99th percentiles of κ. Point sizes proportional to bin counts. Axes re-centered at unconditional means.

Table C.2: Demand Estimates Across Specifications

	Specification			
	OLS Logit	IV Logit	Random Coeffs (no micro)	Rand. Coeffs Microdata
	(1)	(2)	(3)	(4)
A. Price coefficients				
Base price sensitivity	−0.668	−3.030	−0.076	−1.790
	(0.133)	(1.010)	(2.960)	(0.859)
Low income × Price	–	–	1.070	−1.710
			(1.050)	(0.365)
Mid income × Price	–	–	−0.616	−1.070
			(14.600)	(0.299)
High income × Price	–	–	−2.470	−0.014
			(30.600)	(0.404)
B. Distance effects				
Distance (km)	–	–	−0.988	−0.492
			(3.320)	(2.540)
C. Hospital characteristics				
Congestion (SD)	0.252	0.554	0.131	0.363
	(0.163)	(0.231)	(0.492)	(0.297)
Congestion Sq. (SD)	−0.122	−0.138	−0.302	−0.150
	(0.104)	(0.138)	(0.317)	(0.134)
Staff (SD)	−0.280	−0.090	−0.289	−0.189
	(0.153)	(0.140)	(0.544)	(0.235)
No. Specialties (SD)	0.439	0.377	0.386	0.494
	(0.214)	(0.262)	(0.660)	(0.302)
D. Taste heterogeneity				
Private × Insurance	–	–	−0.618	3.100
			(39.100)	(0.658)
Private × Chronic	–	–	0.771	−1.380
			(12.700)	(0.588)
E. Hospital–type fixed effects (Base: Public Specialist)				
Public Non-Specialist	0.720	1.300	0.728	1.340
	(0.482)	(0.581)	(1.200)	(0.755)
Private Maternity Centers	0.947	7.590	−1.740	5.640
	(0.480)	(2.760)	(6.000)	(3.010)
Private Large Hospitals	0.228	8.430	−2.180	5.610
	(0.340)	(3.350)	(16.000)	(3.610)
Private Small Hospitals	−1.280	6.360	−4.530	3.200
	(0.259)	(3.120)	(15.200)	(3.530)

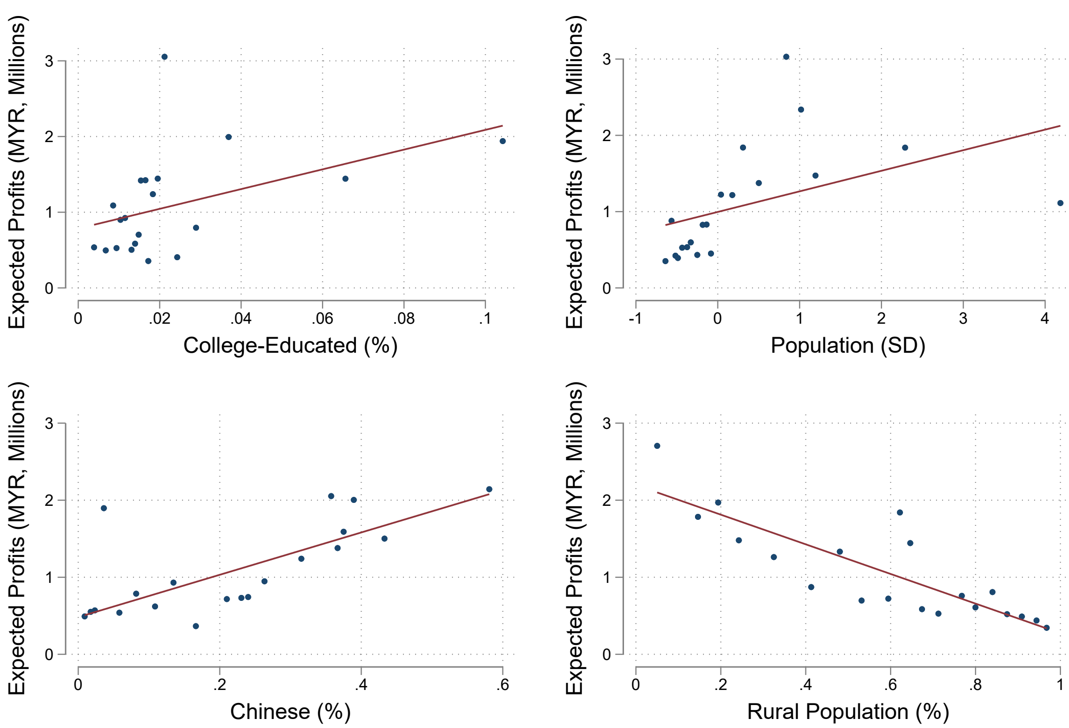
Notes: Robust s.e.'s in parentheses. SD = variable is z-scored. The baseline for hospital-type fixed effects is Public Specialist. Column (2) uses Gandhi and Houde (2019) instruments. Columns (3)–(4) allow random coefficients on *price* and the *private-hospital* dummy; in (4) price sensitivity is fully loaded on demographics (income-group specific). Column (4) additionally matches income, insurance and chronic-condition micro moments from NHMS survey data. Private hospitals set income-group-specific prices in the preferred specification (4).

Table C.3: Estimated Micro Moments (Column 4)

Moment	Observed	Estimated	Difference	Observations
A. Income–Private Hospital Interactions				
$E[\text{low}_i \mid \text{private}_j]$	0.076	0.079	-0.003	5,440
$E[\text{high}_i \mid \text{private}_j]$	0.688	0.681	$+0.007$	5,440
B. Insurance and Chronic Condition Interactions				
$E[\text{insurance}_i \mid \text{private}_j]$	0.602	0.598	$+0.004$	5,440
$E[\text{chronic}_i \mid \text{private}_j]$	0.633	0.635	-0.002	5,440

Notes: Micro moments are conditional expectations computed from NHMS survey data across all markets. Differences are Observed minus Estimated. Values are rounded to three decimal places. Income shares refer to proportions of private-hospital users from each income group.

Figure C.5: Binscatter of Expected Profits in 1996 by District Characteristics



Notes: These binscatter plots show how expected profits estimated from the BLP demand estimates vary by district characteristics as a form of robustness check. The top left panel shows the relationship between expected profits and the proportion of college educated individuals in the district. Top right shows against population, top left against the Chinese population (the ethnic group that is most likely to seek private health care) and bottom right against rural population.

Table C.4: Demand Estimates Across Specifications (Robustness Check by Removing Hospitals with Missing Price/Admissions)

	Specification			
	OLS Logit	IV Logit	Random Coeffs (no micro)	Rand. Coeffs Microdata
	(1)	(2)	(3)	(4)
A. Price coefficients				
Base price sensitivity	−0.491	−1.610	0.000	−0.476
	(0.075)	(0.596)		(0.695)
Low income × Price	–	–	0.363	−1.380
			(2.260)	(0.501)
Mid income × Price	–	–	−1.600	−0.622
			(6.560)	(0.303)
High income × Price	–	–	−0.716	0.561
			(7.510)	(0.411)
B. Distance effects				
Distance (km)	–	–	−0.639	−0.740
			(7.840)	(2.510)
C. Hospital characteristics				
Congestion (SD)	0.235	0.379	0.127	0.114
	(0.106)	(0.147)	(0.290)	(0.305)
Congestion Sq. (SD)	−0.145	−0.175	−0.125	−0.215
	(0.074)	(0.086)	(0.447)	(0.136)
Staff (SD)	−0.065	0.032	−0.037	−0.082
	(0.077)	(0.108)	(0.211)	(0.203)
No. Specialties (SD)	0.208	0.113	0.077	0.304
	(0.158)	(0.192)	(1.050)	(0.338)
D. Taste heterogeneity				
Private × Insurance	–	–	1.280	3.530
			(33.300)	(1.130)
Private × Chronic	–	–	2.610	−1.530
			(20.900)	(0.671)
E. Hospital–type fixed effects (Base: Public Specialist)				
Public Non-Specialist	0.100	0.236	0.106	0.356
	(0.313)	(0.358)	(1.130)	(0.767)
Private Maternity Centers	0.857	3.950	−0.448	1.340
	(0.301)	(1.630)	(3.570)	(2.560)
Private Large Hospitals	0.154	4.040	−3.140	0.523
	(0.217)	(2.080)	(14.900)	(2.940)
Private Small Hospitals	−1.070	2.460	−4.990	−1.550
	(0.177)	(1.830)	(16.000)	(2.810)

Notes: Robust s.e.'s in parentheses. This table uses a restricted sample that excludes hospitals with missing prices or admissions. SD = variable is z-scored. The baseline for hospital-type fixed effects is Public Specialist. Column (2) uses instruments. Columns (3)–(4) allow random coefficients. Column (4) additionally matches micro moments from NHMS survey data.

Table C.5: Top 10 Diagnoses in Private Hospitals (2013)

Rank	Diagnosis Code	Description	N Patients	Percent (%)
1	**O80**	**Normal Delivery**	**45,907**	**5.94**
2	A09	Diarrhoea and Gastroenteritis	30,673	3.97
3	A90	Dengue Fever	23,387	3.02
4	K29	Gastritis and Duodenitis	22,114	2.86
5	J18	Pneumonia	21,426	2.77
6	B34	Viral Infection of Unspecified Site	20,255	2.62
7	O82	Delivery by Elective C-Section	19,581	2.53
8	J20	Acute Bronchitis	12,601	1.63
9	M51	Intervertebral Disc Disorders	11,367	1.47
10	N20	Kidney Stone	11,151	1.44

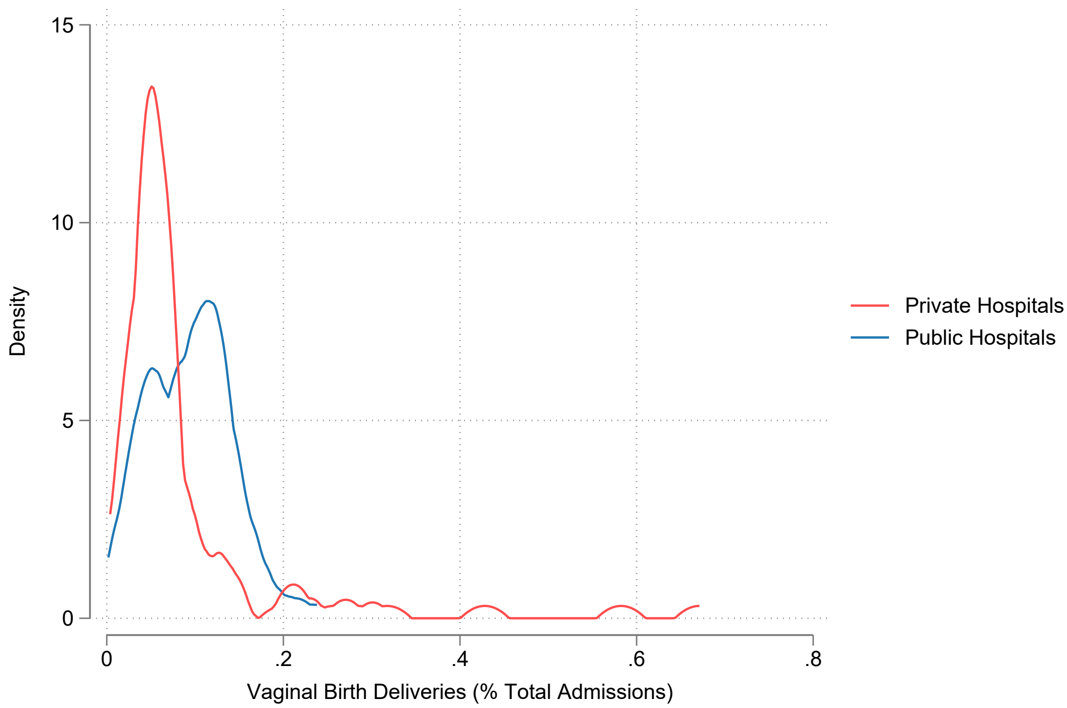
Notes: This table lists the top diagnoses in private hospitals with their corresponding ICD-10 codes, descriptions, patient counts, and percentages of total diagnoses.

Table C.6: Top 10 Diagnoses in Public Hospitals (2013)

Rank	Diagnosis Code	Description	N Patients	Percent (%)
1	**O80**	**Normal Delivery**	**176,582**	**10.66**
2	J18	Pneumonia	68,441	4.13
3	P59	Neonatal Jaundice	61,790	3.73
4	A90	Dengue Fever	37,787	2.28
5	A09	Diarrhoea and Gastroenteritis	35,743	2.16
6	O82	Delivery by Elective C-Section	30,927	1.87
7	J45	Asthma	27,512	1.66
8	E14	Unspecified Diabetes Mellitus	23,888	1.44
9	S06	Intracranial Injury	23,794	1.44
10	I20	Angina Pectoris	23,670	1.43

Notes: This table lists the top diagnoses in public hospitals with their corresponding ICD-10 codes, descriptions, patient counts, and percentages of total diagnoses.

Figure C.6: Birth Share Density



Notes: This figure shows the density of birth shares across public and private hospitals in Malaysia.

Table C.7: Robustness of Entry Cost Estimates to Discount Factor and Planning Horizon

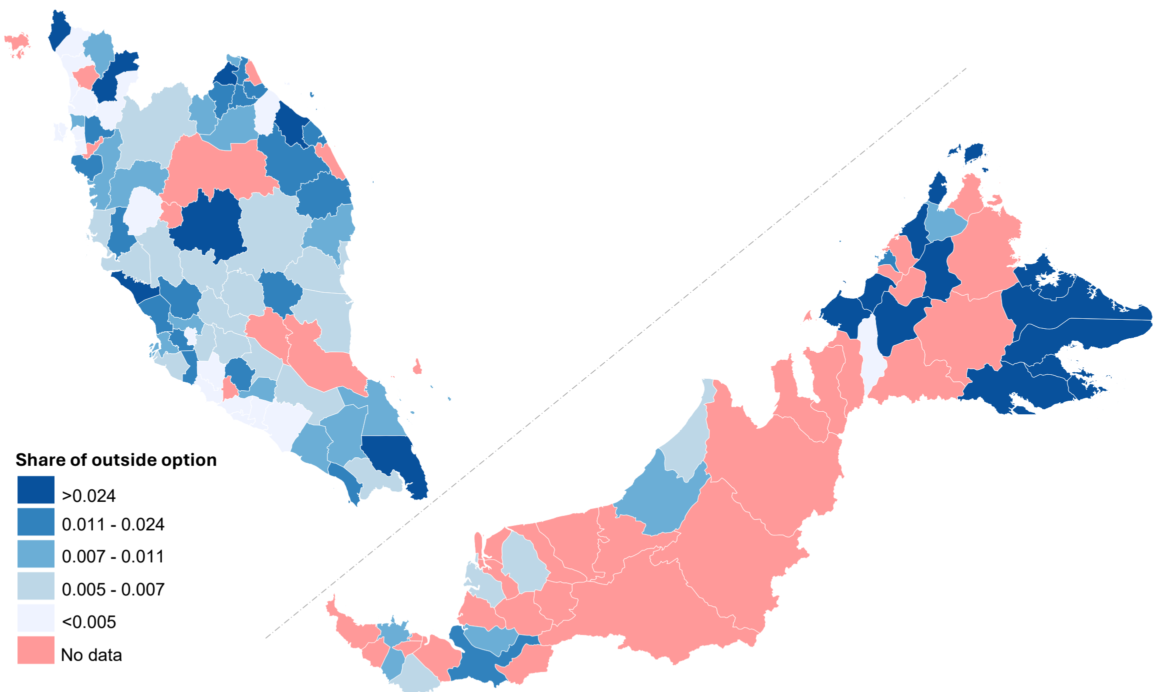
	Mean κ (million MYR)	γ_3	SE	Specialist Effect (million MYR)	% Reduction
Panel A: Varying discount factor ($T = 20$, $\lambda = 0$)					
$\beta = 0.90$	3.82	-20.662	(3.986)	-1.13	29.6%
$\beta = 0.95$ (baseline)	5.09	-27.887	(5.428)	-1.53	30.0%
$\beta = 0.99$	6.68	-36.967	(7.260)	-2.02	30.3%
Panel B: Varying planning horizon ($\beta = 0.95$, $\lambda = 0$)					
$T = 15$	4.59	-25.129	(4.873)	-1.37	29.9%
$T = 20$ (baseline)	5.09	-27.887	(5.428)	-1.53	30.0%
$T = 25$	5.41	-29.600	(5.756)	-1.62	29.9%

Notes: Each row reports results from a separate estimation of the BBL two-step model with $R = 500$ simulation paths. Specialist effect computed as $\gamma_3 \times 54.7$ (the estimated physician supply increase from one specialist public hospital). Percentage reduction computed relative to mean κ in each specification. Year fixed effects included in all specifications. Standard errors clustered by district.

Figure C.7: Selected Maternity Package Posters

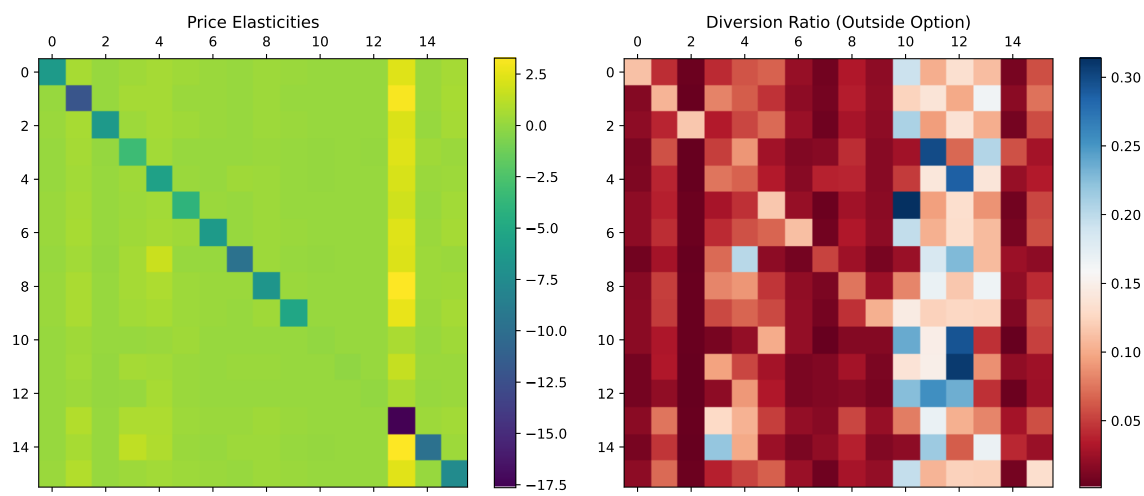
Notes: These posters advertise the maternity packages offered by private hospitals in Malaysia. The packages typically include prenatal care, delivery services (normal or C-section), postnatal care, and sometimes additional services such as ultrasounds or newborn care. Prices vary based on the hospital's location, reputation, and the specific services included in the package.

Figure C.8: Surveyed Districts and Share of Outside Option



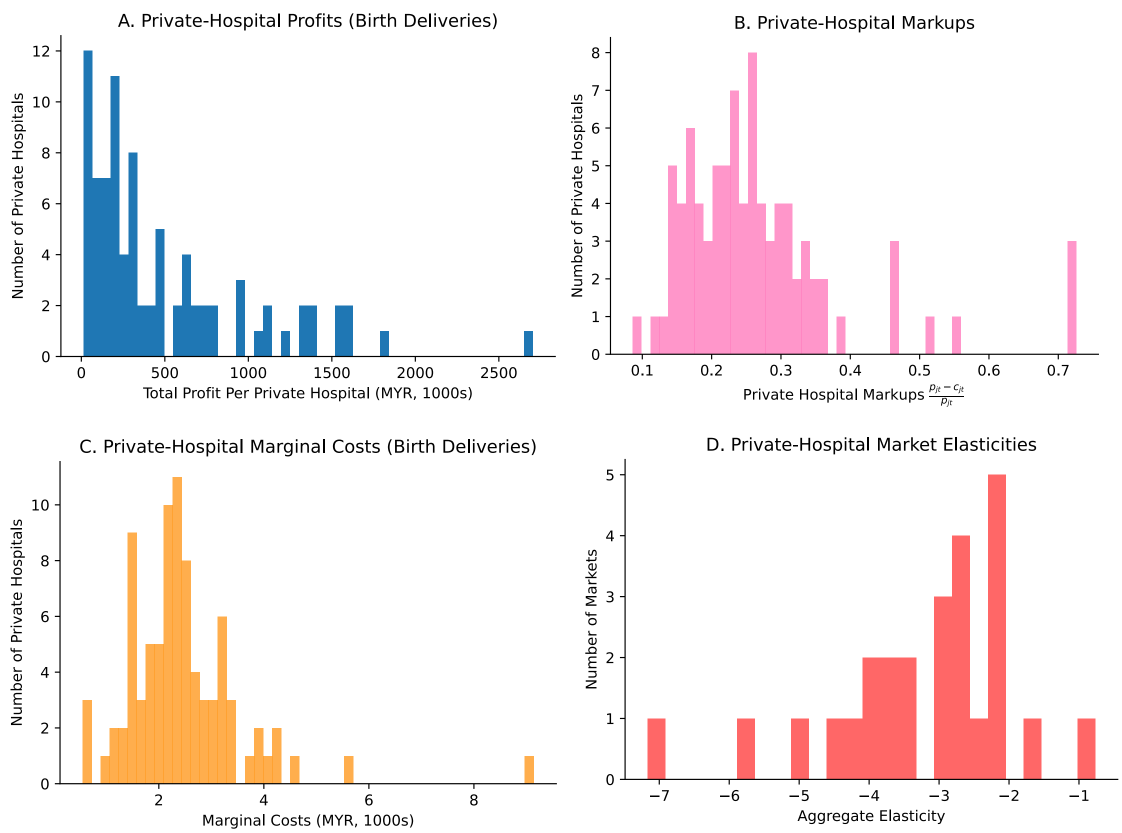
Notes: This map shows the surveyed districts in Malaysia and the share of the outside option (i.e., the proportion of patients seeking care in traditional/home births) for each district. Districts that are shaded pink are districts that were not surveyed and are omitted from the demand estimation.

Figure C.9: Estimated Price Elasticities and Diversion Ratios for the Kuala Lumpur District



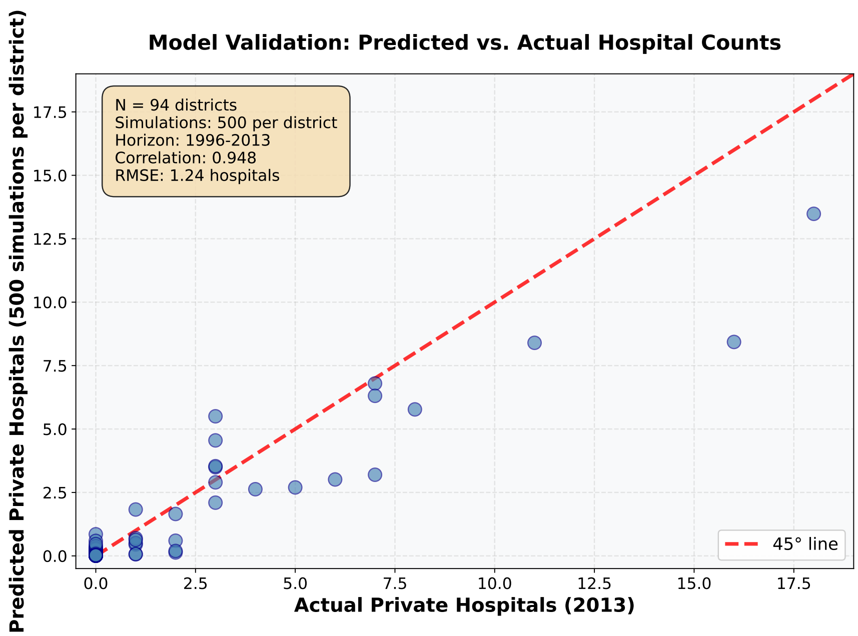
Notes: Price elasticities $\varepsilon_{jk} = \frac{\partial s_k}{\partial p_j} \frac{p_j}{s_k}$ measure the percentage change in market share of product k in response to a one percent change in the price of product j. Own-price elasticities (diagonal elements) are negative, while cross-price elasticities (off-diagonal) are typically positive. Diversion ratios $\mathscr{D}_{jk} = -\frac{\partial s_k}{\partial p_j} \Big/ \frac{\partial s_j}{\partial p_j}$ measure the proportion of consumers who switch from product j to product k when the price of product j increases. Diagonal elements show diversion to the outside good.

Figure C.10: Estimated Profits, Markups, and Elasticities



Notes: Hospital profits computed as $\pi_f = \sum_{j \in J_{fd}} (p_{jt} - c_{jt}) s_{jt}$, representing total profits for ownership group f from all owned hospitals in market d. Markups derived from Bertrand first-order conditions as $\eta = p - c = \Delta^{-1} s$, where $\Delta = -\mathscr{H} \odot \frac{\partial s}{\partial p}'$ captures demand substitution patterns between hospitals under common ownership and $\mathscr{H}$ is the hospital ownership matrix. Marginal costs computed as $c = p - \eta$. Price elasticities $\varepsilon_{jk} = \frac{\partial s_k}{\partial p_j} \frac{p_j}{s_k}$ measure patient demand responsiveness to hospital price changes.

Figure C.11: Model Validation: Predicted vs. Actual Private Hospital Counts (2013)



Notes: Each point represents one district. Predicted counts are obtained by simulating entry decisions forward from 1996 initial conditions using estimated conditional choice probabilities and state transition functions, averaged over 500 simulations per district. Actual counts are from 2013 panel data. Correlation between predicted and actual counts is 0.947; RMSE is 1.25 hospitals.