Competing Complements in Public-Private Hospital Markets

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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 in Malaysia using staggered public hospital construction from 1996 to 2013. Specialist public hospitals increase private entry by 46 percent while non-specialist hospitals reduce it by 27 percent. This heterogeneity reflects labor market spillovers. Specialist hospitals expand the local supply of trained specialists, while non-specialist hospitals do not. A dynamic entry model shows specialist hospitals reduce private entry costs by 19 percent through this channel. Despite complementarities incentivizing entry, counterfactual simulations show competition intensifies in equilibrium, lowering private prices and profits. Whether public provision crowds out or crowds in private investment thus depends on the balance between competition and complementarities.

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1 Introduction

When governments provide goods and services that compete directly with the private sector, public provision typically crowds out private investment. This is shown across multiple sectors as public health insurance expansions reduce private coverage (Cutler and Gruber, 1996; Gruber and Simon, 2008), while public school expansions reduce private enrollment (Dinerstein and Smith, 2021). Crowding out occurs as subsidized public options compete away private demand, reducing private revenues below the threshold needed to justify entry. However, the literature has studied settings where public and private providers are substitutes. In hospital markets across many countries, public facilities often bundle service delivery with workforce training, creating potential labor market complementarities absent from other contexts. Whether these complementarities can offset direct competition remains an open question with significant policy implications, particularly in low- and middle-income countries where public resources are constrained but healthcare capacity is lacking relative to healthcare demand.

These questions are important to health system design in low- and middle-income countries. Governments face an allocation decision of whether to invest directly in public hospitals, or encourage private sector growth. The conventional view that public provision crowds out private investment suggests a trade-off where public expansion may simply substitute for private capacity that would have occurred. But if public hospitals can crowd in private investment, public spending has multiplier effects that expand total healthcare capacity beyond what government alone can provide. Understanding when each outcome occurs is important for health ministries allocating constrained budgets.

Hospitals are large-scale investments,[1] and mixed public-private provision is the global norm.[2] An important distinction between hospitals and other sectors where public provision crowds out private investment is the structure of specialist physician labor markets. Private hospitals require specialist physicians such as surgeons, obstetricians, and cardiologists to offer the services that justify entry. Yet specialists cannot practice immediately after passing board examinations. They must first complete years of residency training under the supervision of existing specialists in accredited public facilities. Public hospitals typically hold monopoly or near-monopoly positions over this training infrastructure, and specialists trained in public hospitals can later practice privately either by leaving public service entirely or by holding dual appointments that allow them to work in both sectors.

This bundling of healthcare delivery with workforce training creates two opposing channels through which public hospitals affect private entry. The competitive channel

[1]Hospitals account for 39 percent of health expenditure across OECD countries

[2]The US relies primarily on private hospitals with public provision concentrated in veterans' affairs and safety-net facilities. European countries like Germany and France maintain mixed systems under regulated insurance frameworks. Large developing countries including India, Brazil, and Indonesia depend heavily on private hospitals alongside public systems.

functions similarly to other sectors, reducing private demand through subsidized care. The complementary channel is specific to hospital markets. Public hospitals serve as essential training centers where specialist physicians complete mandatory residencies, expanding the local supply of specialists and reducing private hospitals' recruitment costs. The net effect depends on which channel dominates. If training spillovers are modest relative to demand substitution, crowd-out results as in other public provision contexts. If training spillovers substantially reduce private entry costs, crowd-in becomes possible.

In this paper, I study this question using Malaysia's public hospital expansion between 1996 and 2013. Malaysia offers an ideal setting for three reasons. First, public hospitals hold a strict monopoly on specialist training, so every specialist practicing in Malaysia is first trained in a public facility. Second, Malaysia's public hospital system includes both specialist hospitals that train residents and non-specialist hospitals that do not, providing variation in whether public facilities generate training spillovers. Third, Malaysia has a combination of active public hospital construction and reliable private sector data. Developed countries have largely completed their hospital infrastructure, with new construction limited to replacements or consolidations rather than market entry (Alexander and Richards, 2023). On the other hand, developing countries that are building hospitals typically lack data on private hospital operations. Malaysia built 25 new public hospitals during this period with data on both sectors, allowing me to observe how public investment affects private market structure.

To identify the causal effects of public hospital construction on private entry, I exploit the staggered timing of hospital openings across Malaysia's districts and a novel dataset combining administrative records, survey data, and primary data collection. No single source covers both public and private hospital in Malaysia, so I construct a district-year panel by linking administrative records on public hospital construction timing and type to private hospital entry counts compiled from survey data. The key identification assumption is parallel trends in private entry, specifically that districts receiving new public hospitals would have experienced similar private entry trends as never-treated districts in the absence of public construction. Several features of the setting support this assumption. Public and private hospitals select locations based on different factors. Public hospitals prioritize underserved areas lacking existing facilities, while private hospitals target areas with population growth and ability to pay. The political origins of the construction program further support exogeneity. 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 private entry incentives. Nevertheless, I conduct extensive robustness checks including event study pre-trends, synthetic difference-in-differences, and matching estimators to ensure that my main results are not spurious.

Across all public hospital types, new construction increases private hospital entry by 47 percent on average, but this average effect obscures opposing effects. Specialist public hospitals, which train specialist physicians through residency programs, crowd in private entry by 61.5 percent. Non-specialist public hospitals, staffed primarily by general practitioners without specialist training programs, crowd out private entry by 56 percent. The heterogeneity maps directly onto the two aforementioned channels. Specialist hospitals generate labor market spillovers large enough to offset their competitive effect on demand, while non-specialist hospitals compete without producing offsetting complementarities. This pattern suggests that the crowd-out findings from other public provision contexts extend to hospital markets, except when public facilities hold monopoly positions in workforce training that create complementarities for private entrants.

Three additional results support the interpretation that both channels exist but at different magnitudes. First, I provide suggestive evidence on the mechanism using census data on private self-employed physicians as an imperfect proxy for private specialist supply and survey data on hospital utilization. Using a 2x2 difference-in-differences design, I find that the pool of private self-employed physicians increases immediately after specialist public hospital construction, and the effect doubles after three years. This timing is consistent with specialists' three-year residency duration. However, specialist public hospitals simultaneously reduce private hospital admissions, suggesting that the competition exists alongside training spillovers. Second, I examine where private hospitals locate within treated districts. Private hospitals avoid entry within 5 kilometers of new specialist public facilities but are more likely to enter in the 10-15 kilometer range. This suggests that patient competition is local as private hospitals avoid co-location with public hospitals while specialist labor spillovers are district-wide, allowing private hospitals to benefit from expanded physician supply without competing directly for patients. Third, I exploit an alternative treatment of public hospital bed capacity upgrades. Between 2003 and 2013, 35 existing specialist hospitals expanded bed capacity without adding new training positions. Consistent with the training mechanism, I find no significant effect of capacity upgrades on private hospital entry.

The reduced-form evidence shows that specialist hospitals crowd in private entry while non-specialist hospitals crowd out. To directly quantify these mechanisms, and decompose private entry incentives into demand substitution and cost reduction channels, 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 19 percent through expanded specialist supply, lowering the initial physician hiring costs of setting up a new private hospital. Non-specialist hospitals generate no such cost reductions, so private entry declines due to competition.

To assess welfare implications, I simulate counterfactual public hospital allocations. Starting in 1996, I introduce one public hospital with median characteristics into each district and simulate equilibrium entry, prices, and market shares forward to 2013. I conduct the analysis separately for specialist and non-specialist public hospitals and report averages across districts with baseline private hospital presence. The simulations show that the entry of a specialist public hospital intensifies competition in the private sector. Private hospital entry increases, private prices decline by 8 percent, and aggregate private profits fall by 30 percent, reflecting reduction in profit margins and business-stealing despite higher private utilization. In contrast, the entry of a non-specialist public hospital leads to greater segmentation between public and private providers[3]. Private prices rise by 14 percent, private market share declines, and total private profits fall by 18 percent. Specialist public hospitals lower private entry costs and intensify competition, while non-specialist hospitals primarily intensify competition without reducing entry costs.

Overall, the tension between crowding in and crowding out private investment depends on the relative effects of competition and complementarities. When public and private providers are substitutes, public provision crowds out private investment as prior work demonstrates. When public facilities bundle goods and services with input production that benefits private entrants, the net effect depends on whether input complementarities offset demand substitution. In hospital markets, specialist training is the key 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 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 market provision across multiple sectors including education (Epple and Romano, 1998; Hoxby, 2000; Dinerstein and Smith, 2021), health insurance (Duggan and Scott Morton, 2006; Curto et al., 2019; Saltzman, 2023), broadband (Wilson, 2025) pharmacies (Atal et al., 2024) and consumer goods (Jiménez Hernández and Seira, 2022). My finding that public hospitals crowd in private hospitals contrasts with classic crowd-out results in health insurance, where Medicare expansions reduce private coverage (Cutler and Gruber, 1996; Gruber and Simon, 2008). Recent evidence shows crowd-in is possible under specific conditions. Andrabi et al. (2024) find that increased public school funding increases private school quality through

[3]Such market segmentation results were similarly shown by Atal et al. (2024) for Chilean pharmacies

competitive pressures. My contribution is identifying labor market spillovers as a distinct mechanism for crowd-in effects.

My empirical findings also contribute to the literature on mixed public-private competition, which examines markets where public and private firms compete directly. Most theoretical work in this area focuses on mixed duopoly models where public firms maximize welfare while private firms maximize profits (Cremer et al., 1991; Matsumura, 1998; De Donder and Roemer, 2009; De Fraja and Valbonesi, 2009; Laine and Ma, 2017; Klumpp and Su, 2019). In healthcare specifically, studies have examined quality competition between public and private hospitals under price regulation (Herr, 2011; Sanjo, 2009), location choices in mixed hospital markets (Hehenkamp and Kaarbøe, 2020), and the welfare effects of market concentration when public and private providers coexist (Bisceglia et al., 2023). However, this literature has been largely theoretical, with limited empirical evidence on the competitive conduct between public and private providers. My paper provides empirical evidence on mixed public-private competition by estimating the causal effects of public hospital entry on private hospital investment decisions. The findings show that competitive outcomes in mixed markets depend on the specific characteristics of public providers, particularly whether they generate complementarities that benefit private competitors.

My results also contribute to the broader literature on place-based policies (Glaeser and Gottlieb, 2008; Freedman, 2013; Busso et al., 2013; Kline and Moretti, 2014; v. Ehrlich and Overman, 2020; Juhász et al., 2024), which typically emphasizes subsidies (Cingano et al., 2023), labor policy changes (Criscuolo et al., 2019), or historical infrastructure projects (Mitrunen, 2024; Garin and Rothbaum, 2024) as policies to stimulate regional economic development. In contrast, my findings highlight how public provision can act as an alternative place-based investment that stimulates private sector investments. Public hospitals crowd in private hospitals by reducing hiring constraints through workforce training. This complementarity shows that place-making policies can extend beyond conventional infrastructure or tax subsidies to strategically placed public facilities that strengthen local markets and generate spillover effects for private investment.

Finally, this paper contributes to the hospital competition literature by examining a setting outside the United States. Most of the literature in the United States emphasizes insurance-driven negotiated prices (Kessler and McClellan, 2000; Ho, 2009; Gaynor et al., 2014; Ho and Lee, 2017, 2019; Shepard, 2022). In many developing countries, patients often pay for hospital care out-of-pocket, and public healthcare play a prominent role in shaping local market structures. Consequently, this difference creates challenges in extrapolating US-based studies to global healthcare markets. While prior research in India underscores the importance of understanding the role of informal providers, mixed payment mechanisms, and trust in healthcare markets (Das and Hammer, 2007; Das et al., 2008; Wagner et al., 2019; Banerjee et al., 2024; Jain, 2024), and studies in China highlight how policies have encouraged public and private hospitals to compete for patients (Eggleston et al., 2008), few have studied the demand and supply decisions of both public and private providers in a lower- or middle-income country context. This paper's novelty is in assessing the trade-offs of public hospital allocation policies in a mixed hospital market.

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. I provide a conceptual framework based on the descriptive facts in Section 4, and then present the reduced form results in Section 5. Section 6 estimates the model to recover the entry costs, and Section 7 details the counterfactuals of adding a new specialist or non-specialist hospital to each district. Section 8 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.[4] 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 the 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

[4] 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).

developed hospital markets where private hospitals operate as an expensive alternative to a heavily subsidized public system, rather than as replacements for public provision.

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 Regulation, Physician Training, and Private Hospital Pricing

Public hospital allocation follows a multi-tiered process embedded within Malaysia's five-year development planning cycle. In the first stage, hospital funding is allocated to districts based on the Malaysia Plans, which are comprehensive 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 emphasizing health care accessibility). After districts receive funding allocations through this centralized planning process, the second stage involves selecting specific locations within the designated district. Local health authorities work with district officials to identify location 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 more lax 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.

Like many developing countries where the public sector dominates healthcare provision, Malaysia requires all physicians to complete a mandatory two-year housemanship program in public hospitals before practicing independently. This creates a direct pipeline from public hospital training programs to employment in both sectors. After completing housemanship, physicians choose between public sector employment (offering civil service job security and fixed salaries) and private practice opportunities with fee-for-service compensation.

Specialist training follows the same pattern. All physicians seeking specialization must complete residency programs in public hospitals, regardless of where these specialists plan to practice afterward. This institutional arrangement allows specialist public hospitals to serve dual purposes. Hospitals serve as both healthcare providers and essential training centers for the entire healthcare labor market, producing personnel who subsequently work across both public and private sectors.

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, any inpatient condition treated in a public hospital costs Malaysian citizens MYR 100 (approximately USD 24) for a normal delivery 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. As a result, private hospitals charge significantly higher prices than public hospitals.

2.3 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 spanning 132 districts over 1996-2013. 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 comes from the Population and Housing Census for 1970, 1980 and 1991. 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.

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.4) 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 come 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 elicits stated preferences about hospital choice for delivery, including quality perceptions (measured on Likert scales), waiting time concerns, and other choice factors. 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.3 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 hospitals across 14 districts) 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 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[5] 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.

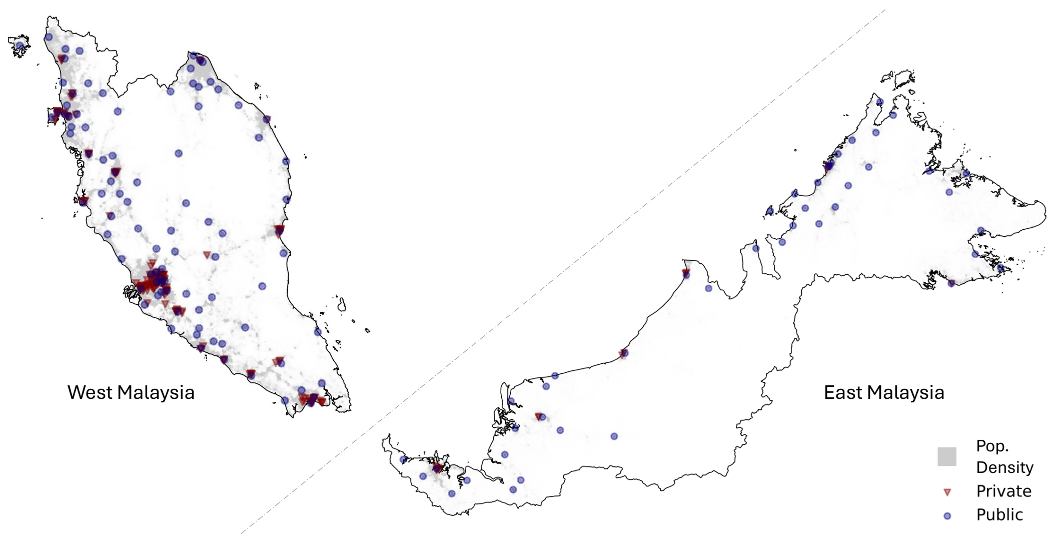
3 Descriptive Facts

In this section, I lay out some key facts about the public-private hospital market in Malaysia. 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.

Despite their urban concentration, private hospitals operate at a significantly smaller scale and capture limited market share. Private hospitals average only 94 beds compared to 509 beds for public specialist hospitals, though similar in scale to non-specialist public hospitals (89 beds). 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. This small market share occurs despite public specialist hospitals

[5]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).

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. 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).

The limited overlap between public and private hospitals partly reflects their focus in segmented price markets. Private maternity services cost 3,306 MYR compared to 100 MYR for subsidized public services. 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).

These differences extend to location decisions. Before estimating the causal effects of new public hospitals on private entry, I examine whether public hospital placement correlates with factors that also drive private entry decisions. If public and private hospitals systematically locate in similar types of districts, this could confound my identification strategy. Figure 2 presents the average marginal effects of various district characteristics on the probability of public and private hospital entry from a logit model with year fixed

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. These are selected statistically significant coefficients from the regression output. Standard errors are clustered at the district level.

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 distinct location patterns. 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. Notably, factors that strongly predict private entry such as population and rurality show weaker or statistically insignificant associations with public hospital allocations. While this descriptive evidence does not rule out all potential confounding, it suggests that public hospital placements are not primarily driven by the same profit considerations that incentivizes private hospital entry.

4 Conceptual Framework

Given the descriptive facts from Section 3, I provide a framework to show how a new public hospital affects private hospital entry. The framework highlights the competition and complementarities between the public and private sector.

Market Setup Consider a geographically distinct healthcare market initially serviced by one public hospital. The public hospital operates with two types of capacity investments: bed capacity K_g^B for patient care and training capacity K_g^T for physician education programs. Public hospitals serve a dual function of providing healthcare services to patients while simultaneously training new physicians through mandatory residency and specialty programs. Increasing bed capacity K_g^B would decrease demand for private entrants, while increasing K_g^T would thicken the labor pool of physicians.

Private Hospital Costs and Entry Decisions A set of potential private hospital entrants $h \in \mathcal{H}$ considers market entry based upon heterogeneous fixed entry costs F_h, independently drawn from a known cumulative distribution $G(F)$. Private hospitals face two types of fixed costs. First, F_s is the sunk cost of obtaining land and constructing a new hospital building. Second, $F_o(L^t)$ is the fixed operational cost that depends on the number of physicians within a market. Increasing the physician labor pool reduces these fixed costs as hiring physicians becomes easier: $F_o'(L^t) < 0$. The fixed operational cost represents the minimum number of physicians the hospital must hire to provide healthcare services. The profit function for private hospital h is:

$$\Pi_h = D_h \cdot (p_h^* - c_h) - F_s - F_o(L^t) \tag{1}$$

where D_h represents demand for private hospital services, p_h^* is the profit-maximizing price, and c_h represents variable costs. Private hospitals enter when expected profits exceed their total fixed costs, giving the entry condition:

$$F_s + F_o(L^t) \leq \pi_h^*(K_g^B, K_g^T) \tag{2}$$

where $\pi_h^*(K_g^B, K_g^T) = \max_{p_h} \pi_h$ represents maximum achievable private profits as a function of local physician supply L^t. Given the distribution of entry costs $G(F)$, the equilibrium number of private entrants is $N = G(\pi_h^*(K_g^B, K_g^T))$.

Crowd-In versus Crowd-Out Mechanisms The relationship between public hospital capacity and private entry operates through two primary channels that work in opposite directions. Public hospitals consist of two distinct types of capacity: bed capacity K_g^B that determines how many patients can be treated, and physician training capacity K_g^T that determines how many doctors can be trained simultaneously. Public hospital bed capacity directly affects the demand available to private hospitals through competition: $\frac{\partial D_h}{\partial K_g^B} < 0$. Public training capacity affects the local specialist physician labor supply that private hospitals need to hire from: $\frac{\partial L^t}{\partial K_g^T} > 0$ and $\frac{\partial F_o}{\partial L^t} < 0$.

Labor Market Crowd-In Effect. Public hospitals increase the local supply of trained physicians L^t through their mandatory training programs. When public hospital training capacity K_g^T expands, it increases physician supply, which reduces private hospitals' fixed operational costs $F_o(L^t)$, making entry more profitable:

$$\frac{\partial N}{\partial K_g^T} = \underbrace{\frac{\partial N}{\partial F_o}}_{(-)} \cdot \underbrace{\frac{\partial F_o}{\partial L^t}}_{(-)} \cdot \underbrace{\frac{\partial L^t}{\partial K_g^T}}_{(+)} > 0 \quad \text{(Labor Market Crowd-In)} \tag{3}$$

Competition Crowd-Out Effect. When public hospital bed capacity K_g^B expands, it takes away demand from the private sector by providing more accessible public care, reducing private hospital profitability:

$$\frac{\partial N}{\partial K_g^B} = \underbrace{\frac{\partial N}{\partial D_h}}_{(+)} \cdot \underbrace{\frac{\partial D_h}{\partial K_g^B}}_{(-)} < 0 \quad \text{(Competition Crowd-Out)} \tag{4}$$

When new public hospitals are constructed, both bed capacity and training capacity typically increase simultaneously. The overall effect on private entry is:

$$\frac{\partial N}{\partial(\text{New Public Hospital})} = \underbrace{\frac{\partial N}{\partial K_g^B} \cdot \Delta K_g^B}_{\text{Competition Effect}} + \underbrace{\frac{\partial N}{\partial K_g^T} \cdot \Delta K_g^T}_{\text{Labor Market Effect}} \tag{5}$$

where ΔK_g^B and ΔK_g^T represent the increases in bed and training capacity from new hospital construction. Crowd-in effects dominate when:

$$\underbrace{\frac{\partial N}{\partial K_g^T} \cdot \Delta K_g^T}_{\text{Labor complementarities}} > \underbrace{\left| \frac{\partial N}{\partial K_g^B} \cdot \Delta K_g^B \right|}_{\text{Competition effects}}$$

This occurs when physician complementarities from thickened labor markets are large relative to bed capacity expansion. Crowd-out effects dominate when bed capacity expansion significantly reduces private demand and physician complementarities are weak. The framework generates two main testable predictions. First, new public hospitals should have heterogeneous effects on private hospital entry depending on the relative strength of physician training versus service capacity expansion. Second, crowd-in effects should be stronger for new hospitals that significantly expand local physician training.

5 Reduced Form Evidence

5.1 Impact of New Public Hospitals on Private Entrants

Identifying the impact of new public hospitals on private entrants requires addressing the endogenous placement of public facilities. The Ministry of Health strategically allocates public hospitals based on accessibility to existing health facilities, population size, and congestion at public facilities. These same factors may also drive private entry decisions and confound causal estimates. Figure 2 provides reassurance that public and private hospitals respond to distinct location incentives. Public hospitals are allocated to districts lacking existing public facilities and urban areas, while private hospitals locate in districts with high population growth, urban settings, educated populations, and established private specialist networks. This suggests that while some overlap exists in location preferences, public placement prioritizes accessibility and filling gaps, while private entry follows profitability.

This motivates a staggered event study design that exploits variation in the timing of public hospital construction. I define treatment units as the 25 districts receiving new public hospitals between 1996 and 2013, and control units as the 22 districts receiving no public hospitals by 2013 (Figure B.1 maps these districts). These never-treated controls will likely receive public hospitals eventually but remain untreated within my observation window. As a robustness check, I also use the last-treated cohort as an alternative control group.

Table 1 compares pre-treatment characteristics between treatment and control districts in 1991. The groups exhibit strong balance on most covariates including wealth distribution, education levels, ethnicity shares, labor force participation, and existing health infrastructure. Chinese ethnicity, which is particularly important given its association with higher private healthcare utilization, appears well-balanced (Ministry of Health Malaysia, 2016). However, treated districts show modest imbalances on three characteristics. Treated districts have significantly larger populations, lower rurality, and are slightly younger.

While I observe modest and only marginally significant imbalances, they could bias my estimates upward since population and urbanization and a younger population could predict higher private hospital entry. I begin with a standard event study specification to transparently assess the magnitude and significance of treatment effects, then verify robustness through balancing regressions, synthetic difference-in-differences (Arkhangelsky et al., 2021) and matching approaches that control for observed differences.

Table 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 and collapsing at the district level (this is different from the survey distances in the structural model, which are self-reported by respondents). Wealth quintiles are constructed from household assets (electricity, water supply, telephone, automobiles, air conditioning, washing machine, refrigerator, television, VCR, radio, toilet, wall material).

I measure my primary outcome as the cumulative count of private hospitals operating in each district-year. My estimation strategy uses the interaction-weighted estimator from Sun and Abraham (2021) to address treatment effect heterogeneity in this staggered adoption setting. Traditional two-way fixed effects estimators are contaminated when treatment effects vary across cohorts and time periods. To address these concerns and ensure my estimates represent interpretable weighted averages of cohort-specific treatment effects, I estimate the following event study specification:

$$Y_{dt} = \delta_d + \lambda_t + \sum_{e \in \mathcal{E}} \sum_{\ell \neq -1} \delta_{e,\ell} \, \mathbf{1}\{E_d = e\} \, D_{dt}^{\ell} + \varepsilon_{dt} \tag{6}$$

where Y_{dt} is the number of private hospitals in district d in year t. δ_d and λ_t are district and year fixed effects. E_d is the year district d receives its first public hospital (with $E_d = \infty$ for never-treated districts). $D_{dt}^{\ell} = \mathbf{1}\{t - E_d = \ell\}$ is an indicator for being ℓ years relative to public hospital opening; and $\mathcal{E} = \{1997, 1998, ..., 2013\}$ represents the set of treatment cohorts. I include relative time indicators for $\ell \in \{-10, ..., -2, 0, ..., 16\}$, and exclude $\ell = -1$ as the reference period. Each coefficient $\hat{\delta}_{e,\ell}$ estimates the cohort-specific average treatment effect on the treated ($CATT_{e,\ell}$) using never-treated districts as the comparison group.

The district fixed effects δ_d absorb all time-invariant differences across districts, such as baseline differences in income levels, population size, or pre-existing healthcare infrastructure that might affect private hospital entry. The year fixed effects λ_t capture shocks that are common to all districts in a given year. Remaining variation comes from comparing how the trajectory of private hospital entry in treated districts changes around the year of public hospital construction, relative to the contemporaneous trends in never-treated districts.

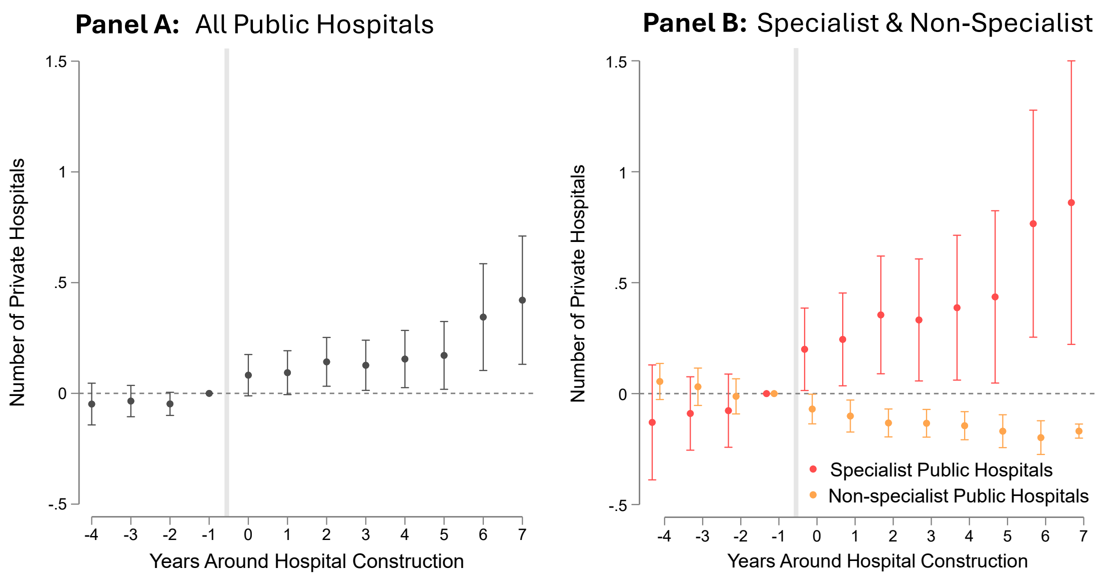
The conceptual framework predicts that the effects of public hospitals on private entry may vary by hospital type. Specialist public hospitals, which provide specialist physician training programs, may generate positive spillovers that encourage private hospital entry. In contrast, non-specialist public hospitals, which primarily offer general inpatient and emergency services, may compete directly with private hospitals and deter entry without offering much complementarities in local labor markets. Thus, I estimate three separate event studies: one pooling all public hospitals, one using only specialist public hospitals as treatment, and one using only non-specialist public hospitals as treatment. For districts receiving multiple public hospitals during the sample period[6], I use only the first treatment for the main analysis and explore robustness below.

In Figure 3, I present the event study estimates of the impact of new public hospitals on the number of private hospitals in the same district. Panel A uses all public hospitals as the treatment, while Panel B splits the treatment to specialist and non-specialist public hospitals. I truncate the figure to show four pre-period lags and seven post-period event

[6] Three districts had more than one public hospitals built between 1996 and 2013.

study estimates, with the reference period at $\ell = -1$. I also provide a table of the average of the full set of post-treatment coefficients in Table 2.

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



Note: This figure presents four period lags and seven post-period event study estimates from Equation 6. The estimates come from the impact of 25 new public hospitals on the number of private hospitals within the same district. Each dot represents a point estimate with the corresponding 95% confidence interval shown as vertical lines. Standard errors are clustered at the district level.

Panel A of Figure 3 shows parallel pre-trends across all hospital types, with coefficients close to zero and statistically insignificant in the four years before public hospital construction. Post-construction, the pooled effect is positive and immediate, with public hospitals increasing private hospital counts by 0.465 on average (Column 1 of Table 2). This is equivalent to a 47.5 percent increase relative to the pre-treatment mean of 0.979.

These pooled estimates mask substantial heterogeneity by hospital type, as shown in Panel B. Specialist public hospitals generate immediate and sustained crowd-in effects, with impacts growing from 0.5 additional private hospitals in year one to over 1.0 by year six. On average across the post-treatment period, specialist hospitals increase private hospital counts by 0.785 (Column 2), representing a 46.2 percent increase relative to the pre-treatment mean of 1.701. In contrast, non-specialist public hospitals produce immediate crowd-out effects that persist throughout the post-treatment period, reducing private hospital entry by 0.3 to 0.5 hospitals across all post-treatment years. The average effect is -0.171 hospitals (Column 3), a 27.1 percent reduction relative to the pre-treatment mean of 0.631.

These opposing signs are consistent with two distinct mechanisms: specialist hospitals may create physician training complementarities that benefit private practice, while non-specialist hospitals may primarily expand basic service capacity that competes directly with

Table 2: Average Post-Treatment Effects on Private Hospitals

	Number of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	0.465		
	(0.094)		
E2: Specialist public hospitals		0.785	
		(0.108)	
E3: Non-specialist public hospitals			-0.171
			(0.009)
Mean Dep. Var.	1.302	1.701	0.631
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N Districts $\times$ Year	846	648	594
R^2	0.951	0.954	0.930
Unique Events	25	14	11
Estimator	SA	SA	SA

Notes: Each column presents results from separate regressions using the Sun and Abraham (2021) estimator. Coefficients represent the average post-period treatment effects from the interaction-weighted estimator. Standard errors in parentheses are clustered at the district level. The dependent variable is the number of private hospitals in a district. Column (1) includes all public hospitals; columns (2) and (3) separate by public hospital type.

private providers. However, the reduced-form effects alone cannot distinguish between alternative explanations. To directly test whether physician training spillovers drive the crowd-in effects of specialist hospitals, I examine impacts on private healthcare utilization and private physician supply below.

5.2 Robustness Checks

To ensure the robustness of the main findings, I conduct several robustness checks that address potential concerns about the empirical design and estimation approach.

Balancing Regressions. I first provide a two-step balancing regression that shows how the event study design addresses endogeneity concerns from the relationship between district demographics, public hospital construction and private hospital entry. To do this, I first predict the number of private hospitals within a district using the same demographic variables in Table 1. Next, I examine how public hospital construction at the district-year level correlates with this predicted measure. The key idea is, if public hospital construction is correlated with unobserved determinants of private hospital entry, then we should see a significant correlation between public hospital construction and the predicted private hospital count. However, if the event study design adequately controls for these confounders, then this correlation should be small and statistically insignificant.

Figure B.3 plots the results. Each set of coefficients represent separate treatment types: all types of public hospitals, specialist public hospitals and non-specialist public hospitals separately. Each dot represents a point estimate from Equation 6, where 'Cross-Section' represents the correlation between public hospital construction and the predicted private hospital count without any fixed effects. The remaining estimates add district fixed effects, year fixed effects, and both district and year fixed effects sequentially.

The results show that without any fixed effects, public hospital construction is positively correlated with predicted private hospital counts, suggesting that public hospitals are more likely to be built in districts with higher underlying demand for private hospitals. However, once I include district fixed effects, this correlation becomes small and statistically insignificant across all treatment types. Adding year fixed effects does not change this result. This evidence suggests that fixed effects effectively controls for confounding factors that might bias the estimates.

Synthetic Difference-in-Differences. The balance table shows some differences in pre-treatment characteristics between treatment and control districts, particularly in population size and rurality. Given this, I test the robustness of my main results using a staggered synthetic difference-in-differences approach (Arkhangelsky et al., 2021). The synthetic DiD estimator addresses key limitations of the standard event study approach by automatically reweighting control districts and time periods based on their predictive power for the outcome. This dual weighting mechanism provides a more credible counterfactual when treatment and control groups exhibit baseline differences, as in my setting. The details on the table and results are in Section B.2.

Table B.3 and Figure B.4 present the results using this method. The findings are consistent with the main specification. Specialist public hospitals significantly increase private hospital entry by 0.692 hospitals on average (compared to 0.785 in the main specification), while non-specialist public hospitals show negligible effects (-0.016 compared to -0.171 in the main specification). The dynamic effects shown in Figure B.4 closely resemble the results from the main event study, with specialist hospitals driving gradual but persistent increases in private entry over time. Though there are some pre-trends visible in the synthetic DiD estimates, the post-treatment effects remain significant and of similar magnitude and direction.

Matching. I also test the robustness of my main results using coarsened exact matching (CEM) to balance treatment and control districts on the two variables showing the largest pre-treatment imbalances: rurality and the number of existing public hospitals. See Section B.3 for details on the balancing, and results.

The matching procedure reduces the sample to 28 districts (12 treated, 16 control), but removes the statistically significant pre-treatment differences (Table B.4). Figure B.5 shows that the effect remains positive and significant at 0.108 additional private hospitals, representing a 31.4 percent increase relative to the matched sample's pre-treatment mean. This percentage effect closely mirrors the main specification (47.5 percent increase), providing additional confidence that pre-treatment imbalances do not drive the results. I focus on all public hospitals for this robustness check rather than disaggregating by type due to the substantial sample reduction that would compromise statistical power for subgroup analysis.

Multiple Treatment Districts. The main analysis uses the first treatment for districts that received multiple public hospitals during the sample period. To test whether this affects my main results, I exclude the three districts that received multiple treatments and re-estimate the main specification. I tabulate the post-treatment event study effects in Table B.5. The results show very similar coefficients to the main effects in Table 2.

Alternative Control Group. The main analysis uses never-treated districts as the control group. As noted above, I re-estimate the main event study results using the last-treated cohort as the control group, which provides a different identifying assumption that compares early-treated districts to those treated at the end of the sample period. I tabulate the post-treatment effects in Table B.6. The results are similar to the main findings, with public hospital entry leading to a significant increase in private hospital entry. Specifically, the introduction of all public hospitals increases private hospital count by 0.760 hospitals on average, representing a 77.6 percent increase relative to the pre-treatment mean of 0.979

hospitals. Specialist public hospitals alone generate an increase of 0.665 private hospitals, a 52.0 percent increase relative to the pre-treatment mean of 1.278 hospitals. However, the analysis for non-specialist public hospitals cannot be estimated due to insufficient variation in the last-treated group, as both control and treatment districts had zero private hospital entrants in this category.

Alternative Estimators. Table B.7 presents results using five different estimators designed for staggered difference-in-differences settings with heterogeneous treatment effects. I compare my main event studies results with the Borusyak et al. (2024) imputation estimator, Callaway and Sant'Anna (2021) group-time aggregation, de Chaisemartin and D'Haultfœuille (2024) estimator, and synthetic difference-in-differences (Arkhangelsky et al., 2021). Across all estimators, specialist public hospitals consistently show positive and generally significant effects on private hospital entry, while non-specialist hospitals show negative effects. The specialist hospital effects range from 0.558 to 1.424, with most estimates statistically significant. Non-specialist hospital effects range from -0.016 to -0.281, all negative but with varying precision.

5.2.1 Mechanism: Effects on Private Health Care Utilization and Private Physicians

To directly test the channels through which public hospitals affect private hospital entry, I examine effects on private healthcare utilization and private physician supply. Unlike the hospital count outcome which uses panel data over the full 1996-2013 period, the mechanism analysis is constrained by data availability. Private hospital admissions data are available for 1996, 2006, and 2011, while private physician data are available for 1970, 1980 and 1991.[7] Given these limited time points, I use a stacked 2×2 difference-in-differences specification rather than the full event study design. For each district d, year t and stack s, I estimate:

$$Y_{sdt} = \beta \cdot \text{Post}_t \times \text{Treated}_d + \alpha_{ds} + \lambda_{ts} + \varepsilon_{dt} \tag{7}$$

where Post_t represents the period after public hospital construction. Treated_d represents districts that received public hospitals during the sample period. α_{ds} are district-by-stack fixed effects, and λ_{ts} are year-by-stack fixed effects. Control units are the same never-treated districts as in the main event study. Treated units are stacked alongside controls, creating two stacks. For admissions, the first stack covers 1996-2006 and the second covers 2006-2011. For physicians, the first stack covers 1970-1980 and the second covers 1980-1991 (Cengiz et al., 2019; Deshpande and Li, 2019). The coefficient β captures the average treatment effect, estimated from within-stack comparisons of treated versus never-treated districts before and after hospital construction.

Market Expansion vs. Substitution Table 3 examines whether public hospitals expand the total healthcare market or primarily substitute for private care. Columns 1-2 show effects on total inpatient admissions (public plus private combined). Specialist public hospitals show no significant effect on total admissions, suggesting the market size remains roughly constant. Non-specialist hospitals similarly show no significant effect on total admissions.

Columns 3-4 suggest the direct substitution effect on private hospital admissions. Specialist public hospitals reduce private admissions by 0.299 per 10,000 admissions (Column 5), a 69.9 percent reduction relative to the pre-treatment private hospital admissions mean of 0.428 per 10,000 admissions. Non-specialist hospitals show a smaller, statistically insignificant reduction of 0.111 (37.9 percent, Column 6). The larger effect for specialist hospitals suggests they offer more direct substitutes for private inpatient services.

Columns 5-6 show how public hospitals affect their public share of total admissions. Specialist public hospitals increase public share of inpatient admissions by 0.241. Relat-

[7] While I do have access to census data from 2000, the lowest level of granularity for physician data combines physicians, veterinarians, dentists and other medical professionals.

ive to the mean of 0.673, this represents a huge market share gain. Combined with the flat total market size, this implies substantial substitution away from private hospitals. Non-specialist hospitals show no significant change in public market share (Column 6). These results together show that public hospitals compete directly with private hospitals for patients, with specialist hospitals generating particularly strong competitive effects. However, if specialist hospitals reduce private hospital revenues substantially, why do they crowd in private entry?

Table 3: Effects of Public Hospitals on Inpatient Admissions

	Total Admissions (10,000s)		**Private Admissions (10,000s)**		**Public Share (%)**	
	(1)	(2)	(3)	(4)	(5)	(6)
E2: Specialist public hospitals	-0.167		-0.299		0.241	
	(0.330)		(0.140)		(0.068)	
E3: Non-specialist public hospitals		-0.369		-0.111		-0.100
		(0.228)		(0.099)		(0.189)
Mean Dep. Var.	1.409	0.842	0.428	0.293	0.673	0.654
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120	114	120	114	120	114
R^2	0.871	0.834	0.815	0.804	0.693	0.654

Notes: Stacked difference-in-differences estimates using National Health and Morbidity Survey (1996, 2006, 2011). Columns 1–2 report total inpatient admissions per 10,000 population (public + private). Columns 3–4 report private inpatient admissions per 10,000 population. Columns 5–6 report the public share of total inpatient admissions. Standard errors clustered by district in parentheses.

Physician Supply Spillovers Table 4 provides evidence for the complementarity channel. Columns 1–2 show effects on total physician supply. Specialist public hospitals increase total physicians by 191.7 from a mean of 114.5 physicians. This huge effect is not surprising, as a new specialist public hospital often employs up to hundreds of doctors. Non-specialist hospitals however show no significant effect on total physician supply as they are mainly staffed by a mix of nurses, general practitioners, and pharmacists.

Columns 3–4 provide the clearest evidence of physician spillovers. Specialist public hospitals increase private specialist physicians by 108.1. This represents a 263 percent increase relative to the mean of 41.1 specialist physicians. Importantly, Table B.1 shows these effects strengthen at longer lags. By lag three, the coefficient doubles to 1.081. This pattern is consistent with residency specialist training programs taking several years to graduate specialists who then enter private practice. Non-specialist hospitals show essentially no effect on specialist physician supply (Column 6).

Columns 5-6 examines whether specialist hospitals increase the share of physicians working in private specialist practice. Specialist hospitals increase the private specialist share by 27.5 percentage points (Column 3), a 126 percent increase relative to the baseline mean of 0.218. This large proportional increase reflects that many districts initially have zero or very few private specialists. Non-specialist hospitals again show no effect on private specialist share.

It is important to note that my data does not distinguish between specialist physicians who dual practice in public and private settings versus those who work exclusively in private practice. However, the large increase in private specialist physicians following specialist public hospital construction strongly suggests that many specialists transition to private practice through either channels. The large effect for specialist hospitals directly validates the labor market complementarity mechanism. Specialist hospitals train specialist physicians who subsequently work at or establish private hospitals, reducing private sector hiring costs and enabling entry despite competition.

Table 4: Effects of Public Hospitals on Physician Supply (3 Years Post-Construction)

	Total Physicians (100s)		**Private Specialist Physicians Physicians (100s)**		**Private Specialist Share of Total %**	
	(1)	(2)	(3)	(4)	(5)	(6)
E2: Specialist public hospitals	1.917		1.081		0.275	
	(1.168)		(0.471)		(0.135)	
E3: Non-specialist public hospitals		-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
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year 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) measuring effects 3 years post-construction to allow specialist residency programs to mature. Columns 1–2: total physicians (in 100s). Columns 3–4: private specialist physicians (in 100s), measured by self-employment; specialists in private practice are predominantly self-employed. Columns 5–6: private specialist physicians as share of total. Standard errors clustered by district in parentheses.

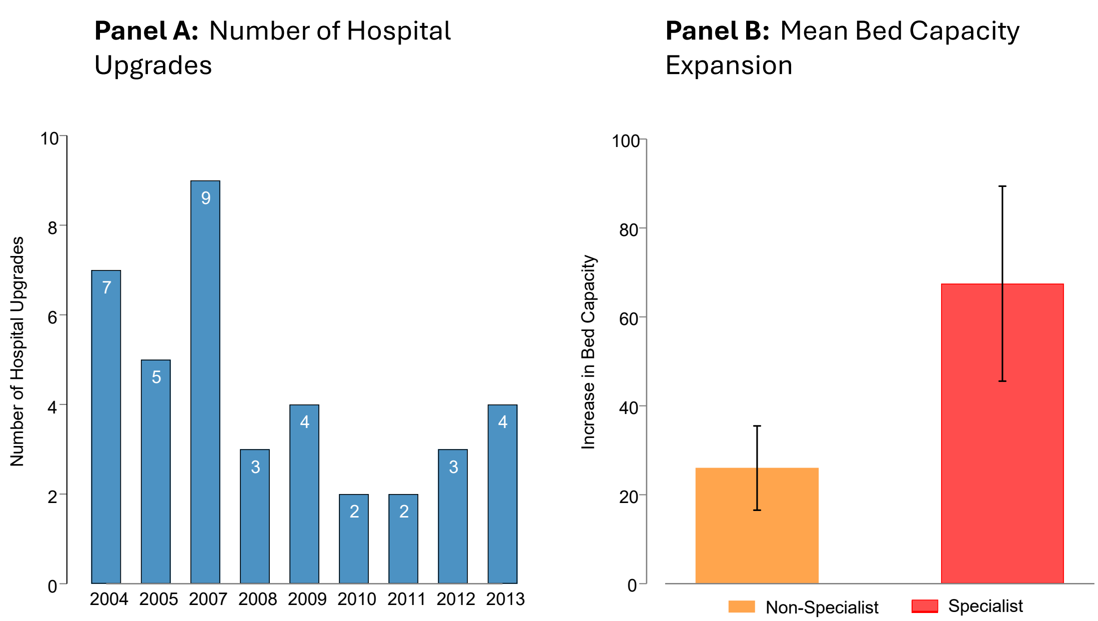
5.3 Impact of Public Hospital Upgrades on Private Entrants

To further test the physician training mechanism, I examine an alternative treatment that expands healthcare capacity without creating new training infrastructure. Public hospital upgrades are defined as expansions of existing facilities through additional bed capacity and provide a sharp test of whether crowd-in effects operate through physician training complementarities or simply through expanded service capacity.

Unlike new hospital construction, which creates entirely new training programs, residency positions, and specialist faculty, upgrades expand the service capacity of existing facilities while generating limited marginal training opportunities. Teaching programs and physician training capacity are already established within these hospitals, so upgrades primarily add beds rather than training slots. If the crowd-in effects identified in the main analysis operate primarily through expanded training opportunities rather than general capacity expansion, hospital upgrades should generate smaller effects than new construction.

Figure 4 shows the distribution of hospital upgrades over time. Between 2003 and 2013 (excluding 2013), 35 public hospitals underwent significant expansions: 24 specialist hospitals and 11 non-specialist hospitals. Panel A plots the number of upgrades by year, while Panel B shows the mean bed capacity expansion per upgrade. I use districts that never received upgrades during this period as control units.

Figure 4: Number of Public Hospital Upgrades by Year



Note: Data on hospital upgrades are from Health Facts published by the Ministry of Health, covering 2003-2013. Hospital upgrades are defined as expansions in bed capacity at existing public hospitals. Panel A shows the number of hospital upgrades by year. Panel B shows the average bed capacity expansion per upgrade.

Table 5 presents the results. The estimates are substantially smaller in magnitude and less precise than the new construction effects. Specialist upgrades increase private hospital entry by 0.238 hospitals (Column 2). This effect is less than one-third the effect of new specialist hospital construction (0.785). The effect is statistically insignificant, with a standard error of 0.215. Non-specialist upgrades show a negative but statistically insignificant effect of -0.170 (Column 3), compared to -0.171 for new non-specialist hospitals.

Table 5: Effects of Public Hospital Upgrades on Private Hospital Entry

	Number of Private Hospitals		
	(1)	(2)	(3)
E1: All upgrades	0.138		
	(0.173)		
E2: Specialist upgrades		0.238	
		(0.215)	
E3: Non-specialist upgrades			-0.170
			(0.169)
Mean Dep. Var.	0.934	1.132	0.631
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1026	846	594
R^2	0.947	0.946	0.928
Unique Events	35	24	11
Estimator	SA	SA	SA

Notes: Each column presents results from separate regressions examining the impact of public hospital upgrades (2003-2013) using the Sun and Abraham (2021) estimator. Hospital upgrades are defined as expansions of existing bed capacities. The dependent variable is the number of private hospitals in a district. Control units are districts that never received upgrades during the study period. Standard errors in parentheses are clustered at the district level.

The difference between upgrade and new construction effects is consistent with the physician training mechanism. Creating entirely new training infrastructure through hospital construction generates large physician supply spillovers that exceed competitive effects. In contrast, marginally expanding existing training capacity through upgrades produces muted effects, as training capacity already exists. While the imprecision of the upgrade estimates precludes strong conclusions, the point estimates suggest that new training infrastructure, and not simply expanded service capacity, drives the crowd-in effects of specialist public hospitals.

5.4 Impact of Specialist Public Hospitals on Private Entry Location

Thus far, the analysis has focused on district-level effects of public hospital entry on private hospital counts. The results show that specialist public hospitals crowd in private entry, while non-specialist hospitals crowd out entry. I now examine where within treated districts private hospitals choose to locate relative to the new public hospital.

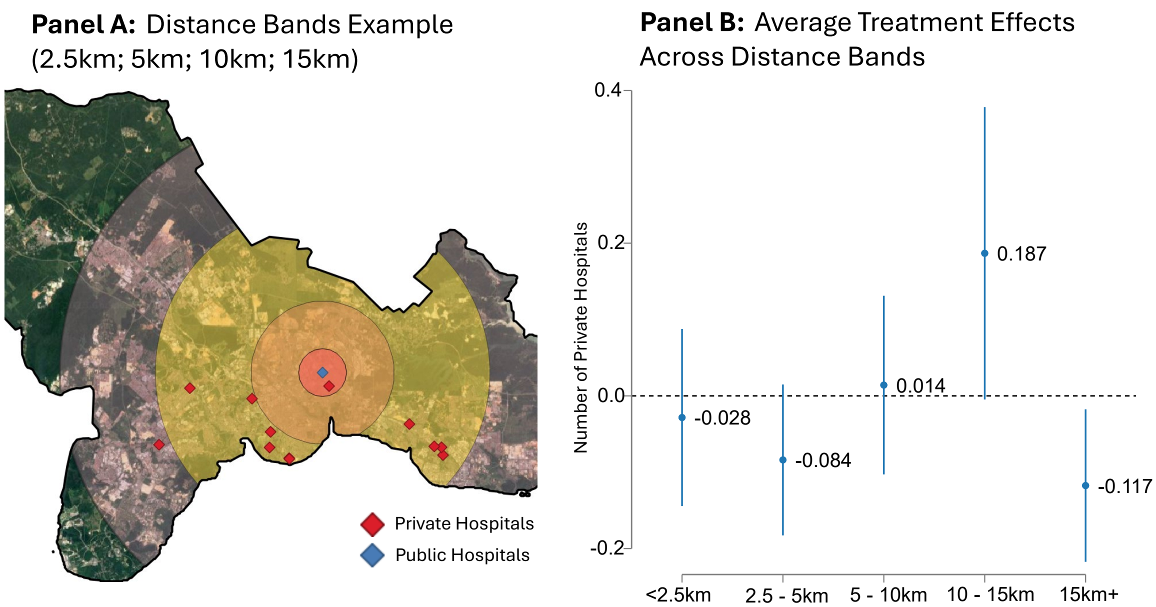
Within the same district, private entrants benefit from physician spillovers generated by a new public hospital. Given this shared labor pool, the spatial distribution of private entry shows how private hospitals balance competing considerations. On one hand, locating near the public hospital intensifies patient competition. On the other hand, locating too far from the public hospital limits access to the shared physician labor pool, as specialist physicians who work across both public and private facilities face commuting constraints. This creates a tradeoff for private entrants between minimizing patient competition and maintaining proximity to trained specialists.

To test this, I estimate the event study specification in Equation 6 using the number of private hospitals within specific distance bands from the newly constructed public hospital as outcomes. I define five mutually exclusive distance bands: 0-2.5km, 2.5-5km, 5-10km, 10-15km, and beyond 15km from the new public hospital. The comparison group is never-treated districts, where I count all private hospitals across the entire district. Panel A of Figure 5 illustrates these distance bands for the 'Johor Bahru' district. Panel B presents the average post-treatment effects across the five distance bands.

The results show a nonlinear spatial pattern of private hospital entry. Within the immediate 0-2.5km vicinity of a new public hospital, private entry decreases slightly, though this effect is not statistically significant. Entry declines sharply and significantly in the 2.5-5km band, with a reduction of 0.084 hospitals. The 5-10km band shows a small positive effect of 0.014 hospitals. In contrast, private entry increases significantly in the 10-15km band, with 0.187 additional hospitals. Beyond 15km, the effect turns negative again, suggesting private hospitals avoid areas too distant from the physician labor pool.

These spatial patterns reconcile the district-level crowd-in effects with patient competition channels. At the district level, specialist public hospitals increase total private entry through physician supply spillovers that dominate demand crowd-out from patient competition. However, within districts, private hospitals strategically sort by distance to balance these competing effects. They avoid the immediate 2.5-10km vicinity where patient competition is strongest, but concentrate in the 10-15km band where they can access the shared physician labor pool while minimizing direct competition for patients. The negative effects beyond 15km suggests that greater distances impose prohibitive commuting costs for dual-practicing specialist physicians, reducing access to the labor market complementarity that drives entry at the district level.

Figure 5: Effects of Specialist Public Hospital on Private Entry Location



Notes: Panel A maps distance band outcomes in the *Johor Bahru* district. The rings represent 2.5km, 5km, 10km and 15km distance from the newly constructed public hospital. Districts with multiple specialist public hospitals constructed during this period are omitted from the sample. Panel B plots the post-treatment estimates using the Sun and Abraham (2021) estimator across five distance bands. Each coefficient represents a separate regression comparing private entry at specified distances in treated districts to total private entry in never-treated districts. The pre-treatment mean number of private hospitals are 0.29, 0.29, 1.43, 0.21, and 0.36 for distance bands 1 through 5, respectively. Standard errors clustered at the district level.

5.5 Heterogeneous Effects by Institutional Context: The Pre-1996 Corporatization Era

The crowd-in effects of specialist public hospitals documented above depend on the institutional context in which they operate. To demonstrate this, I examine whether public hospitals had different effects during the pre-1996 period when the government pursued corporatization policies that threatened to alter the role of public hospitals in the healthcare system.

During the early 1990s, the government proposed corporatizing public hospitals. This policy involves maintaining government ownership but operating them as profit-maximizing entities. The 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. This created substantial policy uncertainty about the future structure of public healthcare delivery. Under corporatization, public hospitals would retain government subsidies while pursuing profits, making them more direct competitors to private hospitals. Additionally, corporatization could alter training spillovers if corporatized hospitals retained trained specialists for their own operations rather than generating spillovers to the broader private sector. The policy environment reversed with the 7th Malaysia Plan (1996-2000), when the government recommitted to purely public healthcare provision and abandoned corporatization.

Table 6 presents event study estimates for public hospital entry during the pre-1996 corporatization era. All types of public hospitals crowded out private hospital entry during this period. Specialist hospitals reduced private entry by 0.035 hospitals, and non-specialist hospitals reduced entry by 0.095. This contrasts with the post-1996 effects where specialist hospitals crowd in private entry by 0.785 hospitals while non-specialist hospitals crowd out entry by 0.171 hospitals.

Several factors may explain the uniform crowd-out during the corporatization era. First, policy uncertainty may have deterred private entry generally, as potential entrants faced ambiguous competition from hybrid public-private entities with unclear competitive advantages. Second, the threat of corporatization could have weakened training complementarities if private hospitals anticipated that corporatized facilities would retain specialists rather than generating spillovers to the private sector. Third, differences in economic conditions between the two periods may have altered private hospitals' entry decisions independently of corporatization policy. While I cannot definitively isolate which mechanism dominates, the reversal from uniform crowd-out to heterogeneous effects demonstrates that institutional context matters. The crowd-in effects of specialist public hospitals documented in the main analysis emerge specifically when public hospitals operate as purely public institutions that train specialists who subsequently enter private practice.

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

	Number of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	-0.084		
	(0.007)		
E2: Specialist public hospitals		-0.035	
		(0.019)	
E3: 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 $\times$ Year	1,024	592	784
R^2	0.886	0.943	0.900
Unique 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. Coefficient estimates are post-treatment effects from the Sun and Abraham (2021) estimator. Standard errors in parentheses are clustered at the district level. The dependent variable is the number of private hospitals in a district. Column (1) includes all public hospitals; columns (2) and (3) separate by public hospital type.

5.6 Heterogeneous Effects by Private Hospital Size

The physician supply mechanism predicts heterogeneous effects across private hospital sizes. If specialist public hospitals crowd in private entry by expanding the local pool of trained specialists, this effect should be strongest for hospitals with lower scale. Small hospitals require fewer specialists to operate, making them more responsive to marginal increases in physician supply. In contrast, large hospitals typically locate in urban areas with pre-existing specialist concentrations, reducing their sensitivity to additional physician supply shocks.

To test this prediction, I estimate Equation 6 separately for two hospital size categories based on bed capacity: small hospitals (fewer than 94 beds) and large hospitals (94 or more beds). Figure 6 presents the event study estimates, with Panel A showing effects of specialist public hospitals and Panel B showing non-specialist effects. Table 7 summarizes the average post-treatment effects.

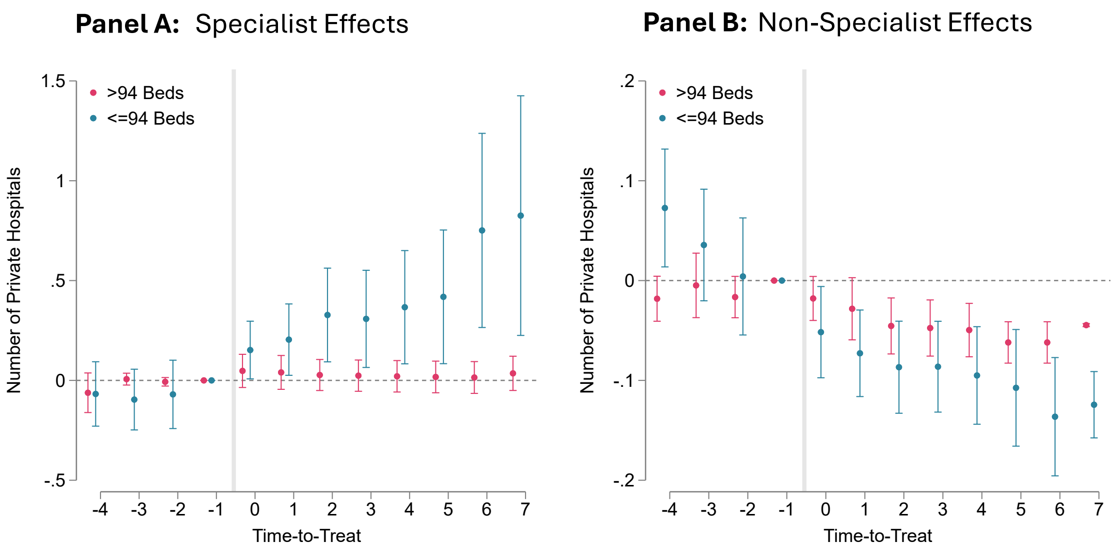
The results show effect heterogeneity by hospital size for specialist hospitals, but relatively uniform effects for non-specialist hospitals. Specialist public hospitals generate strong crowd-in effects on small private hospitals, increasing their count by 0.727 hospitals on average, which is an 80 percent increase relative to the mean of 0.910. In contrast, large hospitals show a modest increase of 0.057 (7 percent relative to the mean of 0.790). These divergent effects show that benefits from expanded specialist physician supply are concentrated among smaller private hospitals.

Several mechanisms explain why small private hospitals respond most strongly. First, small private hospitals face lower entry barriers because they require fewer specialists to reach minimum viable scale. For example, recruiting only a specific specialty like gynecology may suffice for private hospitals that are focusing on maternity services. Second, large private hospitals concentrate in urban areas where specialist supply is already relatively abundant, reducing the marginal impact of additional public training capacity. Third, small specialist hospitals tend to focus on less surgery-intensive services that require smaller clinical teams (Figure B.2).

In contrast, non-specialist public hospitals show relatively uniform crowding out across hospital sizes: reductions of 0.173 for small hospitals (65 percent) and 0.059 for large hospitals (16 percent). The consistent negative effects suggest that competitive pressure from non-specialist public hospitals, which expand general inpatient and emergency services without specialist training programs, operates similarly across the private hospital size distribution. Unlike specialist hospitals, non-specialist facilities generate no offsetting labor supply benefits that might vary by scale, resulting in net crowding out regardless of hospital size.

These heterogeneous effects provide additional support for the physician training mechanism. The specialist physician supply shock generated by public hospitals dispropor-

Figure 6: 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 6. 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% confidence interval shown as vertical lines. The reference period is $\ell = -1$. Standard errors are clustered at the district level.

tionately facilitates entry by small private hospitals, which face lower barriers to reaching operational scale. The uniform crowding out from non-specialist hospitals shows that competitive effects do not vary meaningfully by hospital size in the absence of training complementarities.

Table 7: Effects on Private Hospitals by Size

	Private Hospital Sizes			
	Small (1)	**Large** (2)	**Small** (3)	**Large** (4)
E2: Specialist public hospitals	0.727 (0.085)	0.057 (0.029)		
E3: Non-specialist public hospitals			-0.173 (0.005)	-0.059 (0.002)
Mean Dep. Var.	0.910	0.790	0.268	0.364
Observations	648	648	594	594
R^2	0.911	0.982	0.851	0.980
Unique 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. Coefficients represent the average post-period treatment effects from the interaction-weighted estimator. The dependent variable is the number of private hospitals in each size category within a district. Small hospitals have fewer than 94 beds; large hospitals have 94 or more beds. Columns 1-2 show the effects of 14 specialist public hospitals; columns 3-4 show the effects of 11 non-specialist public hospitals. Standard errors in parentheses are clustered at the district level.

6 Structural Model and Estimation

6.1 Overview

The reduced-form findings show that specialist public hospitals crowd in private entrants by increasing the pool of specialist physicians within districts. In contrast, non-specialist public hospitals crowd out entrants by not providing sufficient complementarities to offset the competitive effects. However, these reduced-form estimates do not quantify how much a new public hospital construction reduces private hospital entry costs, and how it affects private hospitals' profits. Given this, I estimate a model where private hospitals choose which districts (markets) to enter. The decision to enter a market is inherently a forward-looking investment problem. Hospitals enter based on the expectation of a future stream of profits while weighing the costs of entry. This model of oligopolistic entry follows Ericson and Pakes (1995) and Maskin and Tirole (1988).

Figure 7: Model Timeline

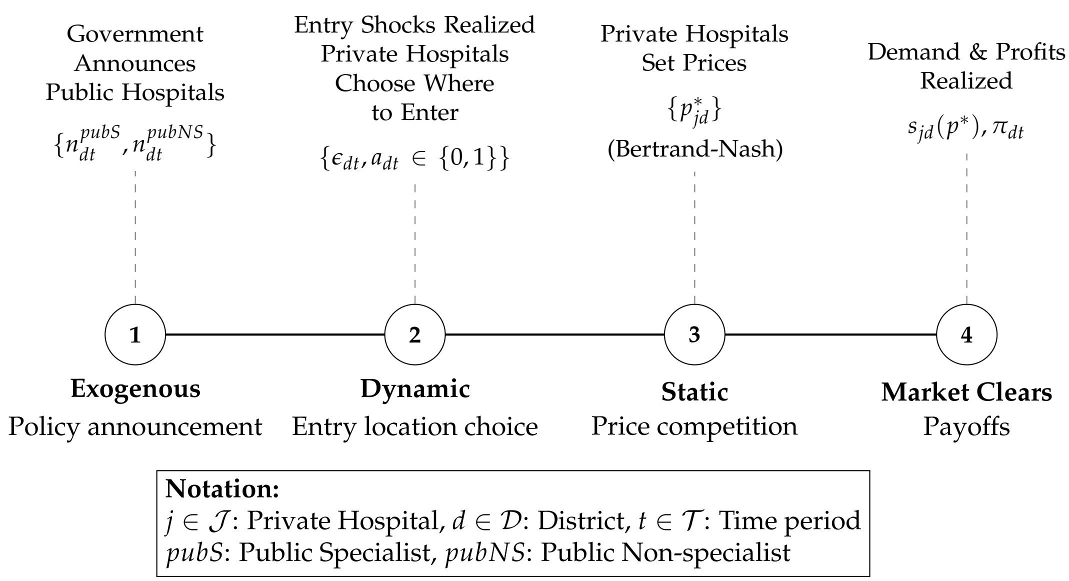


Figure 7 summarizes the timeline. First, the government announces where specialist and non-specialist public hospitals will be built, and private entrants perfectly observe this entire schedule. Second, each potential private entrant draws a specific idiosyncratic entry cost shock and decides whether to enter a district based on future profits, anticipated private specialist physician supply, population growth, and public hospital stocks. Third, after entry decisions are made, incumbent and new private hospitals engage in Bertrand price competition, taking public hospital prices as fixed at 100 MYR. Finally, consumer demand is realized through hospital choices, hospitals earn profits, and states evolve according to transition functions for physician supply and population.

This section follows backward induction logic. I first estimate the second-stage Bertrand price competition in Section 6.2, which determines hospital profits conditional on market structure. I then estimate the first-stage dynamic entry model in Section 6.3, which recovers entry costs using a simplified version of Bajari et al. (2007).

6.2 Second-Stage: Bertrand-Nash Equilibrium and Demand Estimation

I estimate demand using a random coefficients logit model, limiting analysis to childbirth delivery services since I do not observe a full hospital demand system. Focusing on birth deliveries offers four benefits. First, births are the highest volume service in both public and private hospitals (See Table C.6 and Table C.5). Second, private hospitals in Malaysia offer maternity packages where mothers can choose between normal and caesarean section packages (See Figure C.3 for selected maternity promotional posters). This allows me to observe one price per hospital, whereas other conditions may be *ex-ante* unobservable to consumers.

I focus specifically on normal delivery, as caesarean section deliveries are less common and more likely to be influenced by individual medical circumstances. Private health insurance companies in Malaysia do not cover maternity packages, and patients pay out-of-pocket for these services. These demand estimates allow me to calculate hospital-specific total profits from childbirth deliveries, which I scale up based on the share of hospital admissions that are childbirth deliveries at a specific hospital.

Formally, consumer i chooses between a set of hospitals and a maternity center option[8] j within district d for normal deliveries, and faces an outside option of traditional health facilities or home births. The utility for consumer i choosing hospital j in district d is:

$$U_{ij} = \underbrace{\alpha_{g(i)}\, p_j}_{\substack{\text{Price}\\ \text{by}\\ \text{income}\\ \text{group}}} + \underbrace{\lambda_i \,\text{distance}_{ij}}_{\substack{\text{Travel}\\ \text{disutility}}} + \underbrace{\text{private}_j \cdot (Z_i'\mathbf{\Pi})}_{\substack{\text{Preference for}\\ \text{private hospitals}}} + \underbrace{H_j\beta}_{\substack{\text{Hospital}\\ \text{attributes}}} + \underbrace{\xi_j}_{\substack{\text{Unobserved}\\ \text{hospital}\\ \text{quality}}} + \varepsilon_{ij} \tag{8}$$

Where p_j is the price of hospital j and price sensitivity $\alpha_{g(i)}$ varies across income groups $g(i) = \{\text{low, mid, high}\}$. Public hospital prices are all subsidized and priced at MYR 100 or approximately 24 USD, while private hospital prices vary by hospital j. The term λ_i captures the disutility of travel distance to hospital j. distance_{ij} is the distance from consumer i to hospital j. The term private_j is an indicator for private hospitals. The effects are captured by the coefficient vector Π which is interacted with consumer attributes Z_i to allow preferences for private care to vary across individuals.

[8] I take the average characteristics of a maternity center wherever a district has a maternity center, and take the average price nationally. I do this because I do not have a full set of prices across all maternity centers.

H_j is a vector of observed hospital characteristics which consist of congestion levels measured by bed occupancy rates,[9] a squared congestion term, total staff, number of medical subspecialties and a dummy for facility types. Facility types are either maternity centers, public specialist and non-specialist or private small (<94 beds) or large ($\geq$ 94 beds) hospitals. The term ε_{ij} is an i.i.d. type-I extreme value error term. I normalize the utility of the outside option to zero $U_{i0} = 0$.

I face several challenges in missing data and temporal misalignment in consolidating my demand estimation data. In 2013, there were a total of 135 private hospitals alongside 70 maternity centers, and 135 public hospitals. To construct my 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 in my sample, 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.2 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.1 compared to Table C.3).

6.2.1 Estimation and Identification

I estimate the model using generalized method of moments (GMM) through the PyBLP python package (Conlon and Gortmaker, 2020, 2023). Further details of the demand estimation are in Appendix C. The estimation uses a set of moment conditions that matches the model's predicted market shares to the observed market shares and individual choices.

[9] Bed occupancy rates are calculated by dividing the total number of inpatient days by available bed-days over a year. For example, a hospital with 100 beds has 36,500 bed-days in a year (100 beds × 365 days). If the hospital had 25,000 inpatient days in that year, the bed occupancy rate would be 68.5 percent (25,000 / 36,500).

Additionally, I match the share of consumers that choose private hospitals in district d varied by income groups and individual characteristics to the observed shares in the survey data.

To identify price sensitivity $\alpha(g_i)$, the standard concern is that prices may be correlated with unobserved hospital quality. While controlling for observed hospital characteristics H_j helps, I also use an instrumental variable approach. I construct a set of 'sums-of-characteristics' price instruments (Gandhi and Houde, 2019). For each hospital j, I compute the sum of observable characteristics of other hospitals operated by the firm (firms are categorized into the following groups: the government, solo entrepreneurship groups and hospital-chain groups) and those operated by competing firms. These instruments capture exogenous variation in hospital characteristics that shift price but are plausibly orthogonal to unobserved quality. The instruments strongly predict prices, with a first-stage F-statistic of 30.83.

The demand estimates are reasonable (See Table C.1). The preferred specification in Column (4) yields economically sensible parameter estimates that are consistent across model specifications. Price sensitivity decreases with income, distance deters private hospital choice, and hospital characteristics enter with expected signs. Consumers with private insurance favor private hospitals and those with chronic diseases are less likely to choose private hospitals. Comparing across the four specifications, micro moments are important for pinning down these heterogeneous preferences. This is shown by the contrast between imprecise price sensitivity estimates in Column (3) without microdata and the statistically significant coefficients in Column (4). 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.

6.2.2 Hospital Profits and Expected Entry Profits

Given the demand estimates, I compute private hospital profits, markups, and marginal costs assuming Bertrand-Nash competition. I use the demand estimates from Column (4) of Table C.1 as my preferred specification. To align expected profits with 1996 entry decisions, I compute profits based on incumbent hospitals operating by 1996.

I recover hospital-specific marginal costs and profits from the first-order conditions of multi-product Bertrand pricing. Ownership groups include hospital chains (for example, KPJ, Pantai, Columbia Asia, Sime Darby), solo entrepreneurship groups operating independent hospitals, and the government. Given my estimated demand parameters and observed prices, I invert this system to recover marginal costs c_j for each hospital, and then compute hospital-level profits as $\pi_j = (p_j - c_j)s_j M_d$, where s_j is hospital j's market share and M_d is the total number of births in district d. The distribution of these profits and markups are in Figure C.6.

To assess the external validity of my hospital profit estimates, I benchmark them against publicly available annual reports of major hospital groups. However, I acknowledge an important temporal mismatch: my profit estimates are based on 2013 data (deflated to 1996 values), while the available benchmarks come from 2005-2015 annual reports. For KPJ Healthcare, their 2005 annual report indicates an average profit per hospital of approximately RM 2.3 million, which increased to RM 5.8 million by 2015. For IHH Holdings (the parent company of Pantai Hospitals), their 2015 annual report suggests a profit of roughly RM 16 million per hospital. My estimates for KPJ-owned hospitals (RM 8.0 million) and Pantai hospitals (RM 13.7 million) in 2015 fall within a plausible range of these benchmarks, though the temporal mismatch limits direct comparability.

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 use the estimated demand elasticities to recover hospital-level margins, deflate prices and costs to 1996 MYR, and then restrict incumbents to facilities operating by 1996. I maintain 2013 birth volumes rather than backcasting to 1996 levels, as the key variation for identification comes from cross-district differences in market structure rather than temporal trends in birth volumes.

I calculate expected profits for a 1996 entrant from the market share-weighted mean profits of 1996 incumbents for districts with incumbent private hospitals. For districts without private hospitals by 1996, I construct expected profits based on what an average private entrant would earn given the district's market size. I compute expected profits from entering a district in the following steps. First, I scale hospital-specific birth delivery profits to total annual 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.2). Second, I deflate 2013 prices and costs to 1996 nominal values using the national consumer price index. Third, I aggregate these hospital-specific profits at the district level using only hospitals operating by 1996. For districts with at least one 1996 private hospital incumbent, I compute the market share-weighted mean incumbent profit:

$$\bar{\pi}^{SW}_{d,1996} \equiv \frac{\sum_{j \in I_d^{1996}} s_{jd,2013}\, \pi^{1996}_{jd}}{\sum_{j \in I_d^{1996}} s_{jd,2013}},$$

where $s_{jd,2013}$ are the BLP demand shares and π^{1996}_{jd} 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. 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.

I acknowledge that this 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.

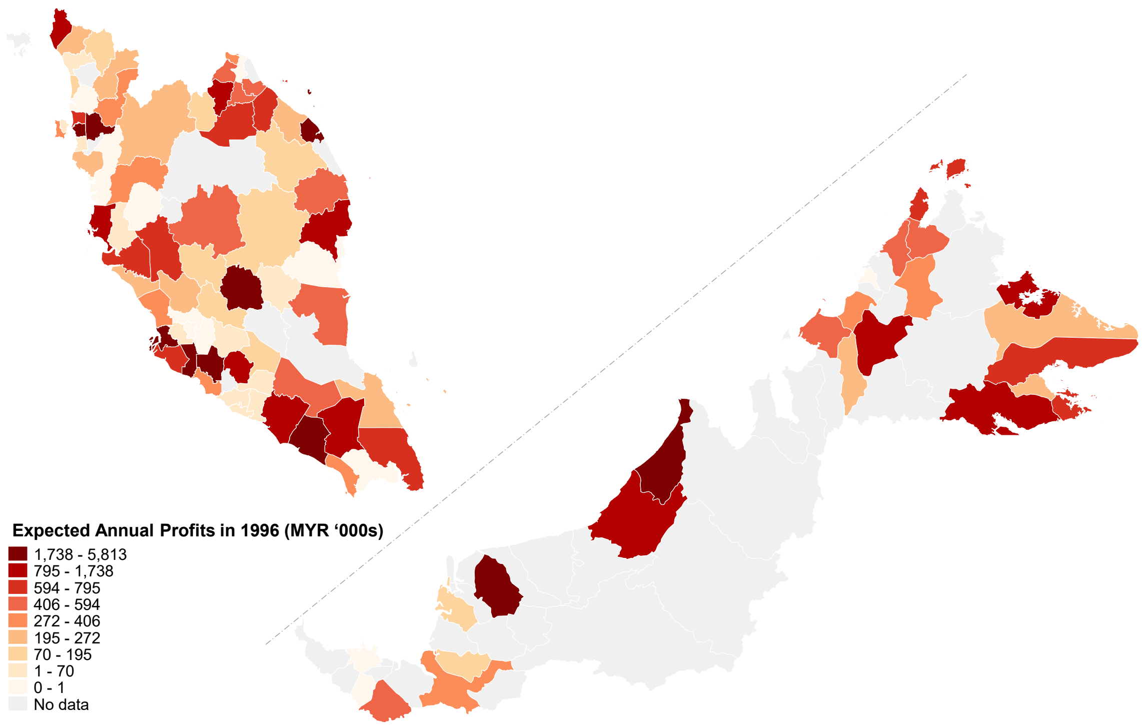
To test the sensitivity of my entry cost estimates to this assumption, I allow market-level profits to vary above or below the baseline through a scaling parameter λ. Expected entrant profit is then:

$$\mathbb{E}[\pi_{d,1996}] = \bar{\pi}^{SW}_{d,1996}\,(1+\lambda),$$

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. I set $\lambda = 0$ in the baseline case and report entry cost estimates under all three scenarios to show robustness. 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.

Figure 8 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.

Figure 8: Expected Profits from Entering a District in 1996



Notes: Expected profits 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, I assume an ‘average’ synthetic private hospital entrant enters into these districts and prices the mean price, and captures the mean market share. Birth volumes maintained at 2013 levels. Public hospital prices fixed at MYR 100.

6.3 First-Stage: A Dynamic Model of Hospital Entry

6.3.1 Overview

Private hospital entry is a forward-looking investment decision where potential entrants weigh current entry costs against expected future profit streams. Hospitals anticipate how market conditions evolve over time as population grows, public hospitals open (bringing both physician supply increases and competitive pressures), and other private hospitals enter. I model entry decisions as a finite horizon dynamic discrete choice problem where private hospitals trade off immediate entry costs against expected future profits.

I estimate this model using a simplified version of Bajari et al. (2007), as my setting only involves entry decisions without exit[10] or investment choices. I model a single potential entrant's binary decision (wait vs. enter) at each district-year, while allowing market structure to evolve as a competitive private entrant enters following estimated entry probabilities. The single-entrant restriction is empirically motivated. No district experienced multiple hospital entries within the same year during 1996-2013. Firms make entry decisions based on Markov-perfect equilibrium strategies, where strategies depend only on payoff-relevant state variables rather than the full history of play.

State Space and Entry Decision At each period t, a potential entrant in district d observes the current state S_{dt} and chooses an action $a_{dt} \in \{0, 1\}$ corresponding to 'wait' or 'enter'. The state vector captures all payoff-relevant information:

$$S_{dt} = \left(n_{dt}^{\text{pri}}, n_{dt}^{\text{pubS}}, n_{dt}^{\text{pubNS}}, \text{docs}_{dt}, \log(\text{pop}_{dt})\right) \tag{9}$$

where n_{dt}^{pri} counts total private hospitals already operating, n_{dt}^{pubS} and n_{dt}^{pubNS} count specialist and non-specialist public hospitals, docs_{dt} measures private specialist physician supply, and $\log(\text{pop}_{dt})$ captures the log of district population.

Entry Costs Entry requires paying a one-time fixed cost that depends on local market conditions. I decompose entry costs into sunk costs (land acquisition, construction) and operational setup costs (recruiting the initial physician team). I specify entry costs as:

$$C_{dt} = \underbrace{\gamma_0 + \gamma_1 \ln(\text{pop}_{dt}) + \gamma_2 \ln(\text{LandPrice}_d)}_{\text{Sunk Costs}} + \underbrace{\gamma_3 \text{docs}_{dt}}_{\text{Operational Setup Costs}} + \delta_t + \epsilon_{jdt} \tag{10}$$

[10] Between 1996 and 2013, Malaysia's private hospital industry experienced zero exits. While there were some hospitals that were acquired or merged, these did not result in market exits. Additionally, some private hospitals downsized or restructured without exiting the market. I do not observe these changes, and thus abstract away from exit decisions.

The coefficient γ_1 captures how population growth increases land prices and construction costs, γ_2 measures baseline land acquisition costs using district-level commercial land prices, and γ_3 measures how specialist physician availability affects operational setup costs. The key hypothesis is $\gamma_3 < 0$. More doctors reduce entry costs by lowering physician recruitment expenses and training requirements. Year fixed effects δ_t capture aggregate shocks (e.g., nationwide healthcare policy changes, macroeconomic conditions), and $\epsilon_{jdt} \sim \text{T1EV}(0, 1)$ is an idiosyncratic cost shock that generates probabilistic entry decisions.

Expected Profits and the Bellman Equation Expected profits for entrants come from the BLP demand model estimated in Section 6.2. For each district d, I compute the expected per-period profit for a new private hospital entrant in 1996, denoted $\mathbb{E}[\pi_{d,1996}]$, using the baseline demand scenario ($\lambda = 0$) where public hospitals do not alter total private sector demand. This baseline profit serves as the input for computing profits in future periods as market conditions evolve. The value function for a potential entrant over a finite planning horizon of $T = 20$ years satisfies the finite horizon Bellman equation:

$$V(S_{dt}) = \mathbb{E}_\epsilon \left[\max\left\{V^{\text{wait}}(S_{dt}),\, V^{\text{enter}}(S_{dt})\right\}\right] \quad \text{for } t = 0, 1, \ldots, T-1 \tag{11}$$

where the choice-specific value functions are:

$$\begin{aligned} V^{\text{wait}}(S_{dt}) &= \beta \mathbb{E}[V(S_{d,t+1})] \quad \text{if } t < T \\ V^{\text{enter}}(S_{dt}) &= \sum_{\tau=0}^{T-1-t} \beta^\tau \mathbb{E}[\pi_{d,t+\tau} \mid S_{dt}] - C_{dt} \end{aligned} \tag{12}$$

with terminal condition $V(S_{d,T}) = 0$ for all terminal states. Per-period profits $\pi_{d,t+\tau}$ evolve from the baseline BLP estimate $\mathbb{E}[\pi_{d,1996}]$ according to the transition equation specified below.

Finite Horizon and Terminal Value I use a finite planning horizon of $T = 20$ years (1996-2015) with terminal value $V(S_{dT}) = 0$ for all states. This specification is justified for two reasons. First, the discount factor places diminishing weight on distant periods. With $\beta = 0.95$, we have $\beta^{20} \approx 0.358$, meaning profits 20 years in the future receive less than half the weight of current profits. Extending the horizon beyond 20 years adds limited value to present discounted profits.

Second, and more fundamentally, entry costs are identified from the value difference $\Delta W = V^{\text{enter}} - V^{\text{wait}}$ rather than absolute value levels. The finite horizon truncation affects both entry and waiting paths, so what matters for the entry decision at $t = 0$ is the near-term value differential captured within the finite horizon. Adding a continuation value would increase both V^{enter} and V^{wait} by similar amounts, leaving ΔW largely unchanged.

State Transitions States evolve according to empirically estimated transition functions. Private specialist physician supply follows an AR(1) process with discrete jumps when public hospitals open. I estimate this process using census data from 1970, 1980, and 1991:

$$\text{docs}_{d,t+1} = \alpha_d + \rho_{\text{doc}} \cdot \text{docs}_{dt} + u_{dt} \tag{13}$$

where α_d captures district-specific baseline physician supply and $\rho_{\text{doc}} = 0.749$ measures persistence (how much of this year's physician stock carries over to next year). The residual standard deviation is $\hat{\sigma}_{\text{doc}} = 15.2$. I incorporate causal effects of public hospital entry from the reduced-form estimates in Table 4. The full transition equation used in forward simulation is:

$$\text{docs}_{d,t+1} = \alpha_d + \rho_{\text{doc}} \cdot \text{docs}_{dt} + \theta_S \mathbb{1}\{\text{new pubS}_{dt}\} + \theta_{NS} \mathbb{1}\{\text{new pubNS}_{dt}\} + \varepsilon_{dt}^{\text{doc}} \tag{14}$$

where $(\theta_S, \theta_{NS}) = (54.7, -6.0)$ are imposed from Table 4 and $\varepsilon_{dt}^{\text{doc}} \sim N(0, \sigma_{\text{doc}}^2)$ with $\sigma_{\text{doc}} = 15.2$. This specification links the structural model to reduced-form evidence: each new specialist public hospital increases private doctor supply by 54.7 physicians, which reduces entry costs through the γ_3 coefficient in equation (10). Population follows a similar AR(1) process:

$$\log(\text{pop}_{d,t+1}) = \alpha_d^{\text{pop}} + \rho_{\text{pop}} \cdot \log(\text{pop}_{dt}) + \varepsilon_{dt}^{\text{pop}} \tag{15}$$

where $\hat{\rho}_{\text{pop}} = 0.875$ governs persistence, α_d^{pop} are district fixed effects, and $\varepsilon_{dt}^{\text{pop}} \sim N(0, \sigma_{\text{pop}}^2)$ with $\hat{\sigma}_{\text{pop}} = 0.048$. Public hospital transitions follow the deterministic schedule announced by the Ministry of Health:

$$n_{d,t+1}^{\text{pubS}} = n_{dt}^{\text{pubS}} + \mathbb{1}\{\text{new pubS}_{dt}\} \tag{16}$$

$$n_{d,t+1}^{\text{pubNS}} = n_{dt}^{\text{pubNS}} + \mathbb{1}\{\text{new pubNS}_{dt}\} \tag{17}$$

I observe public hospital openings through 2013 and assume no new public hospitals open thereafter.

Profit Evolution Post-Entry Once a hospital enters, its per-period profit evolves with market conditions and competitive private entry:

$$\pi_{dt} = \mathbb{E}[\pi_{d,1996}] \times \frac{\text{pop}_{dt}}{\text{pop}_{d,1996}} \times \frac{n_{d,1996}^{\text{pri}} + 1}{n_{dt}^{\text{pri}}} \tag{18}$$

The term $\frac{n^{\text{pri}}_{d,1996}+1}{n^{\text{pri}}_{dt}}$ captures how additional private entrants reduce per-hospital profits. This specification makes three simplifying assumptions. First, it treats marginal private entrants as homogeneous, entering with characteristics similar to existing hospitals rather than optimally choosing differentiation strategies. This assumption is consistent with the entry model, which abstracts from product positioning decisions and treats potential entrants symmetrically. Second, it assumes profits decline proportionally with the number of competitors, approximating a symmetric oligopoly where entrants capture roughly equal market shares. Third, at the point of entry, firms form expectations about profits conditional on market structure rather than observing realized Bertrand-Nash equilibrium outcomes. The baseline profit $\mathbb{E}[\pi_{d,1996}]$ from the BLP demand system represents expected equilibrium profits under the observed 2013 market structure, which potential entrants use to forecast payoffs in future states.

6.3.2 Estimation Strategy: Two-Step BBL Approach

I estimate the model using the Bajari et al. (2007) two-step approach, which avoids solving the full dynamic programming problem by first recovering conditional choice probabilities (CCPs) from observed entry decisions, then using forward simulation to compute value functions. This method is well-suited to my empirical setting, where I observe only binary entry decisions (not investments or exit choices), yielding a simple action space with two alternatives: enter immediately or wait.

To further simplify the two-step approach, recall that I assume cost shocks follow a Type I Extreme Value distribution. This distributional assumption allows further for two key simplifications. First, it generates closed-form logit choice probabilities, allowing me to estimate CCPs nonparametrically from observed entry patterns. Second, it allows for the Hotz and Miller (1993) inversion, which directly relates choice probabilities to value differences without computing conditional value functions. Combined with the linear cost specification in equation Equation 10, this allows me to recover cost parameters through a simple second-stage regression rather than solving a system of moment inequalities, substantially reducing computational burden.

Step 1: Policy Function Estimation I estimate entry probabilities using a binary logit model on observed entry decisions across 92 districts over 1996-2012:

$$\ln\left(\frac{P(\text{enter} \mid S_{dt})}{P(\text{wait} \mid S_{dt})}\right) = \alpha_0 + \sum_{j=1}^{4} \alpha_j \mathbb{1}\{\text{doc bin}_j\} + \alpha_2 n^{\text{pubS}}_{dt} + \alpha_3 n^{\text{pubNS}}_{dt} + \alpha_4 n^{\text{pri}}_{dt} + \alpha_5 \log(\text{pop}_{dt}) \tag{19}$$

Doctor supply enters flexibly through quintile bin dummies (with a separate bin for zero doctors) to capture potential non-linearities. I include the stock of private hospitals n_{dt}^{pri} to control for competition effects, and public hospital stocks to account for how existing public capacity affects entry incentives. Standard errors are clustered at the district level. The estimates are in Table C.4. The estimates align with the reduced-form findings. Private hospitals are more likely to enter areas with private specialist physicians, though the effect is non-monotonic. Controlling for private specialist physician stock, private entrants are less likely to enter markets with more public specialist or non-specialist hospitals, or more private hospitals. Larger populations also increase entry probabilities.

It is worthwhile to note that while a potential entrant private firm makes a one-time binary entry decision, market structure evolves as other private firms enter. In each period, a competitive private firm enters with probability $P(\text{enter} \mid S_{dt})$ drawn from the estimated conditional choice probabilities. This approach allows n_{dt}^{pri} to evolve realistically without requiring a full multi-agent equilibrium model.

Step 2: Finite Horizon Forward Simulation For each initial state $(d, t = 1996)$, I simulate $R = 500$ forward paths over $T = 20$ periods (1996-2015) under two policy scenarios. First, enter immediately at $t = 0$, and second, follow the estimated CCP policy ('wait'). For each simulation path, I draw stochastic shocks for doctor supply and population transitions according to equations (14) and (15), implement the observed public hospital schedule through 2013, and compute period-specific profits using equation (18), which evolves the BLP baseline profit $\mathbb{E}[\pi_{d,1996}]$ forward according to market conditions.

For the 'wait' policy, I implement an optimal stopping rule. At each period before entry occurs, the firm draws an entry decision from the estimated CCP $P(\text{enter} \mid S_{dt})$. If 'wait' is chosen, the simulation continues. If 'enter' is chosen, the firm enters immediately and begins earning profits for the remainder of the horizon. For competing entrants, I model their decisions using the same estimated CCPs, assuming they act as a competitive fringe. At each period, with probability $P(\text{enter} \mid S_{dt})$, another private hospital enters the market, increasing competition.

I set the continuation value to zero at the terminal period $V(S_{d,T}) = 0$ for all terminal states, regardless of whether entry has occurred. This finite horizon specification focuses identification on the 1996-201 window when public hospital construction created exogenous variation in physician supply. Given the discount factor $\beta = 0.95$, the present value weight on periods beyond year 20 is only $\beta^{20} \approx 0.358$, limiting the influence of periods beyond the planning horizon. The total discounted value for each path is $\sum_{t=0}^{T-1} \beta^t \pi_{d,1996+t}$, where $\pi_{d,1996+t}$ equals zero before entry occurs and follows equation (18) after entry, evolving from the BLP baseline $\mathbb{E}[\pi_{d,1996}]$ according to population growth. I average across the $R = 500$ paths to obtain $V^{\text{wait}}(S_{d,1996})$ and $V^{\text{enter}}(S_{d,1996})$ for each initial 1996 state.

Recovering Choice-Specific Value Functions The Type I Extreme Value distribution of cost shocks yields the Hotz-Miller inversion (Hotz and Miller, 1993), which directly relates choice probabilities to value differences:

$$V^{\text{enter}}(S_{dt}) - V^{\text{wait}}(S_{dt}) = C_{dt} + \ln\left(\frac{P(\text{enter})}{P(\text{wait})}\right) \tag{20}$$

Let $\Delta W_{dt} = V^{\text{enter}}(S_{dt}) - V^{\text{wait}}(S_{dt})$ denote the value difference from forward simulation and $\eta_{dt} = \ln(P(\text{enter})/P(\text{wait}))$ the estimated log-odds. Rearranging gives:

$$\kappa_{dt} \equiv \Delta W_{dt} - \eta_{dt} = C_{dt} \tag{21}$$

which represents the revealed entry cost. The intuition is very appealing. κ measures the costs needed to reconcile the simulated value difference ΔW with the observed entry probability (through η).

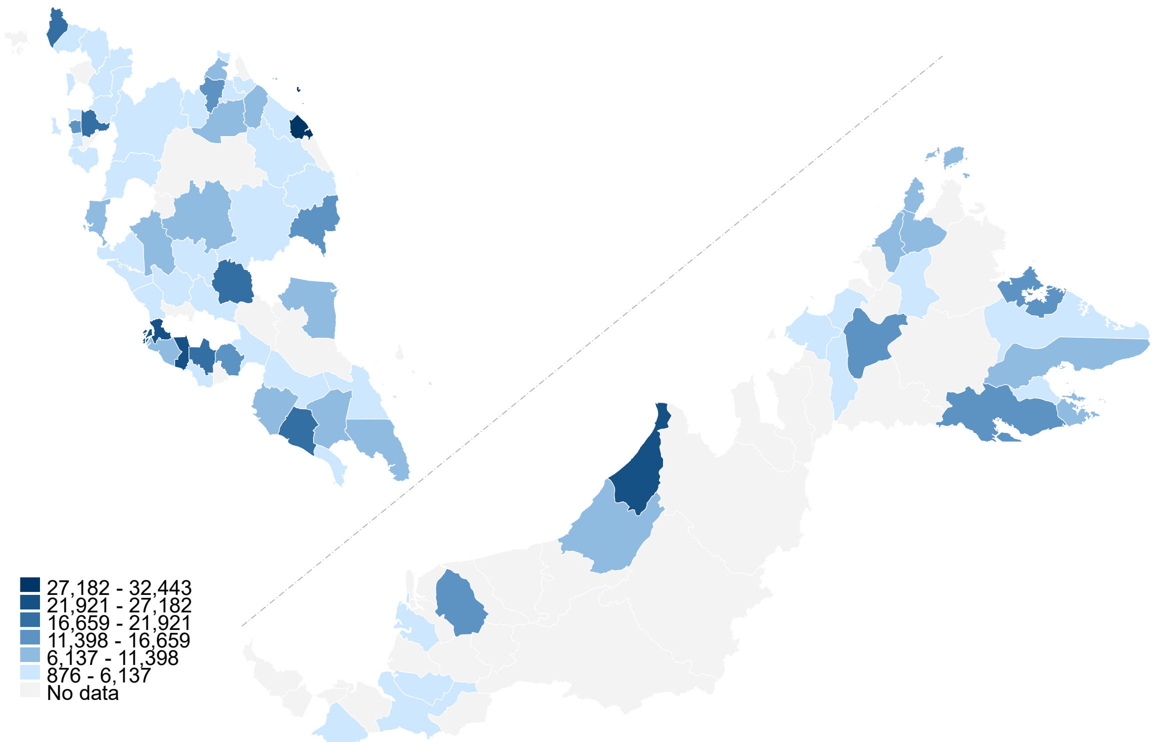
Second-Stage Regression Substituting the cost function from equation (10) into equation (21) yields the second-stage regression:

$$\kappa_{dt} = \gamma_0 + \gamma_1 \ln(\text{pop}_{dt}) + \gamma_2 \text{LandPrice}_d + \gamma_3 \text{docs}_{dt} + \delta_t + u_{dt} \tag{22}$$

I estimate this using OLS with year fixed effects δ_t and standard errors clustered at the district level. The key parameter is γ_3, which measures how private doctor supply affects operational entry costs. The hypothesis is $\gamma_3 < 0$, i.e. more doctors reduce entry costs. When specialist public hospitals increase doctor supply by $\theta_S = 54.7$, operational entry costs fall by approximately $-\gamma_3 \times 54.7$ thousand MYR.

Instrumental Variables Estimation One threat to identifying the cost reduction effects due to increased private specialist labor pool is reverse causality. Districts with higher unobserved entry potential may attract more doctors. I address this using lagged doctor supply from the 1980 census as an instrument. This instrument satisfies relevance (historical physician stocks predict contemporary supply) and plausibly satisfies exclusion (1980 doctor counts affect 1996-2012 entry decisions only through 1996 doctor supply). However, the first-stage F-statistic is 5.0, showing a weak instrument problem. Given this limitation, I interpret the IV estimates cautiously and focus on the OLS estimates, noting that measurement error in physician counts would bias OLS coefficients toward zero, making them conservative lower bounds on the true effect.

Figure 9: Second-Stage BBL Cost Estimates Across Districts in 1996



Notes: This figure displays the revealed entry costs κ_{dt}. Each point represents a district's estimated entry cost in 1996 under the baseline profit scenario ($\lambda = 0$). Mean entry cost is RM 6.54 million; mean annual profit is RM 639 thousand, implying that on average a private hospital would need to operate for approximately 10.2 years to recoup entry costs.

6.4 Results

Figure 9 plots the estimated total entry costs by district in 1996 for an 'average' private entrant. Estimated mean entry costs are approximately 6.5 million MYR (1.5 million USD), while mean annual profits estimated from the demand estimates are approximately 639 thousand MYR (148 thousand USD). This implies that a private hospital would need to operate for approximately 10 years to recoup its entry costs, assuming constant market structure and profits. High entry costs are concentrated in areas lacking existing medical doctors and public hospitals, primarily in rural districts.

Table C.7 tabulates the second-stage entry cost estimates from the finite-horizon model under three profit assumptions. The baseline scenario (Columns 1–2) holds total private profits constant with entry, while alternative scenarios allow profits to expand by 10 percent (Columns 3–4) or contract by 10 percent (Columns 5–6). In the baseline specification, Column 1 shows that average entry costs amount to RM 6.32 million and decline significantly with physician supply. The coefficient of -0.022 indicates that each additional physician reduces entry costs by RM 22,000. Given that specialist public hospitals increase local physician supply by 54.7 doctors on average (Table 4), this implies a reduction in private entry costs of roughly RM 1.20 million, equivalent to a 19.0 percent decline relative to mean costs.

Column 2 presents instrumental variables results. The IV coefficient of -0.024 is consistently more negative than the Column 1 estimate across all specifications, suggesting that measurement error attenuates the baseline estimates. However, given the weak first-stage problem, the IV estimates lack precision. The consistency in sign and approximate magnitude across specifications suggests that severe endogeneity bias is unlikely, though the Column 1 estimates should be interpreted as conservative lower bounds given probable measurement error. Columns 3-6 show that the estimates are stable across profit scenarios. Under optimistic profit expectations, the physician supply effect is -0.025 and -0.027, corresponding to cost reductions of 19.5 to 21.0 percent. Under pessimistic expectations, the effects are -0.020 and -0.022, implying cost reductions of 19.1 to 21.0 percent. Similar results across specifications shows robustness to alternative assumptions about the evolution of the private profit pool.

6.5 Model Validation

Before using the structural model estimates for counterfactual analyses, 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. Specifically, 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.7 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. The 45-degree line represents perfect prediction. Points falling on this line show the model exactly predicts the observed number of 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).

The model performs well across most of the distribution but slightly underpredicts entry in the highest entry districts (those with more than 15 hospitals). This suggests the model may not fully capture agglomeration effects that amplify entry in dense urban markets. These high-entry districts are Kuala Lumpur and Petaling Jaya, which are the largest metropolitan districts where hospitals benefit from unobserved heterogeneity given the parsimonious state specification. Despite this limitation, the strong predictive power does provide some confidence that the structural estimates capture the economic primitives driving hospital entry decisions and that the model can reliably simulate counterfactual public hospital allocation policies.

7 Counterfactuals

In this section, I quantify how public hospital construction affects private market outcomes and to directly show the tension between competition and complementarities. The counterfactuals are not designed to evaluate welfare or the optimal allocation of public hospitals. Instead, they isolate equilibrium responses in private entry, prices, and market shares under alternative public hospital allocations. The analysis focuses on districts with baseline private hospitals (of which there are 24) and only for maternity services, a subset of hospital demand for which prices and utilization are observed. This restricted exercise is also why I do not report welfare outcomes. Full details of the counterfactual procedure are in Appendix D

Table 8 tabulates the effects of adding one additional public hospital of each type to each eligible district and simulating the market forward to 2013. Columns labeled 'Baseline' fix the historical allocation, while 'CF' adds one additional specialist or non-specialist public hospital. For each scenario, I allow private hospitals to enter endogenously and solve for equilibrium private prices conditional on market structure. The table summarizes district-level averages of the resulting 2013 market outcomes, including the number of private hospitals, the private price, private and public shares, the outside option share, and total private profits.

The specialist counterfactual shows how complementarities can exceed competitive effects at the entry margin. Adding a specialist public hospital increases average private entrants from 3.46 to 4.46. Simultaneously, private prices fall from 3,740 to 3,453 MYR and total private profits decline 30 percent from 0.53 to 0.37 million MYR. These estimates show that specialist public hospitals generate cost complementarities that induce private entry despite competition reducing private profits. The non-specialist counterfactual exhibits crowd-out driven by competition without offsetting cost complementarities. Adding a non-specialist public hospital reduces average private entrants from 3.46 to 2.96. Private prices rise from 3,740 to 4,254 MYR, while private market share declines from 5.2 to 3.7 percent. Total private profits fall 17 percent from 0.53 to 0.44 million MYR. On the public side, non-specialist construction increases public share by 4.0 percentage points. The contrast between counterfactuals highlights the mechanism emphasized in the reduced-form analysis. Specifically, specialist public hospitals crowd in private entry through labor-market complementarities that lower entry costs, while non-specialist hospitals primarily shift demand toward the public sector and crowd out private investment.

These counterfactuals are subject to several limitations. First, they are computed for maternity services only, which represent a subset of hospital profits. The magnitude is unlikely to generalize to other products with different competitive conditions and cost structures. Second, physician labor market spillovers enter the model through private entry costs but not through marginal costs or pricing directly, reflecting an interpretation in which specialist availability primarily affects fixed hiring and startup costs rather than ongoing operating costs. Third, the exercise holds hospital median characteristics fixed and abstracts from within-district location choice, endogenous public placement, and alternative hospital scale or timing choices. For these reasons, the counterfactuals should be interpreted as a transparent comparison of specialist versus non-specialist public provision under a common set of assumptions, rather than as an evaluation of an optimal public investment policy.

Table 8: Counterfactual Effects of Adding One Public Hospital in Districts with Baseline Private Hospitals

	Specialist Public Hospital				Non-Specialist Public Hospital			
	Baseline	CF	Δ	Δ (%)	Baseline	CF	Δ	Δ (%)
Private Sector								
N Private Hospitals	3.46	4.46	1.00	29%	3.46	2.96	−0.50	−14%
Private Price (MYR)	3,740	3,453	−287	−8%	3,740	4,254	514	14%
Private Share (%)	5.2	7.4	2.2	–	5.2	3.7	−1.5	–
Total Private Profit (M MYR)	0.53	0.37	−0.16	−30%	0.53	0.44	−0.09	−18%
Public Sector and Outside Option								
Public Share (%)	90.7	91.7	1.0	–	90.7	94.7	4.	–
Outside Share (%)	4.1	0.9	−3.2	–	4.1	1.6	−2.5	–
N Districts		24				24		

Notes: Counterfactual effects of adding one public hospital to each district, simulated forward to 2013. The sample is restricted to districts with ≥ 1 baseline private hospital (N=24). Baseline refers to the historical allocation. CF refers to the counterfactual allocation with one additional public hospital. Private prices and profits are for hospital maternity consumers only. Private price, share, and profits are averages across all private hospitals in these districts. Changes in shares are reported in percentage points, percentage changes are omitted where not meaningful.

8 Conclusion

Existing evidence shows that government provision of goods and services tends to crowd out the private sector. This paper shows that public provision can instead crowd in private investment when complementarities exceed competitive effects. I show this in the context of Malaysia's public hospital expansion between 1996 and 2013. Combining multiple administrative, survey and primary data sources, I find that specialist public hospitals increase private hospital entry, while non-specialist public hospitals reduce entry. I estimate that specialist public hospitals reduce private entry costs by RM 1.26 million (19 percent of mean entry costs) by increasing local physician supply. Counterfactual simulations show that specialist hospitals intensify competition by lowering private prices and profits, yet private entry increases because entry cost reductions dominate these competitive losses. The net crowd-in effect shows that the physician training spillover exceeds demand crowd-out for specialist hospitals. Non-specialist public hospitals generate minimal physician spillovers while competing for patients, leading to a crowd-out effect.

These findings show that public provision can be thought of as a policy tool beyond improving equity. Governments tend to allocate public resources to achieve equity and social objectives such as improving access for underserved populations. Instead, public provision can strategically affect market structure and has implications for equilibrium private response. In this specific context, the findings show that specialist physicians are the key inputs driving entry decisions, and because the public sector controls physician training infrastructure, specialist public hospitals crowd-in private investment through labor market complementarities.

Overall, this paper highlights the importance of accounting for private sector responses when making public spending and provision decisions. A similar idea is shown in Andrabi et al. (2024), which shows that improving public school quality in Pakistan can lead to a multiplier effect from private investment in improving private quality. These findings are particularly important for policymaking in developing countries where healthcare providers consist of both public and private actors, with physicians often working in both sectors and where public hospitals serve as the primary training ground for medical professionals. Given the ubiquity of public-private healthcare systems in many developing countries, understanding these interactions can make public interventions more targeted to local contexts and needs. Depending on whether private investment is desired, specialist hospitals can play a strategic role in stimulating complementary private investment while achieving public health objectives.

Several limitations suggest directions for future research. First, I do not observe or model healthcare quality, which matters for patient welfare. 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 poorer populations who rely on public facilities. Estimating the equilibrium effects of public-private competition 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 generalize to other medical conditions. Third, while the structural model quantifies how physicians affect entry costs, I do not directly observe or model the micro-level physician labor market. Future work incorporating richer data on physician training, specialization choices, and inter-sectoral choices would shed light on the mechanisms generating these spillovers and their distributional consequences.

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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.

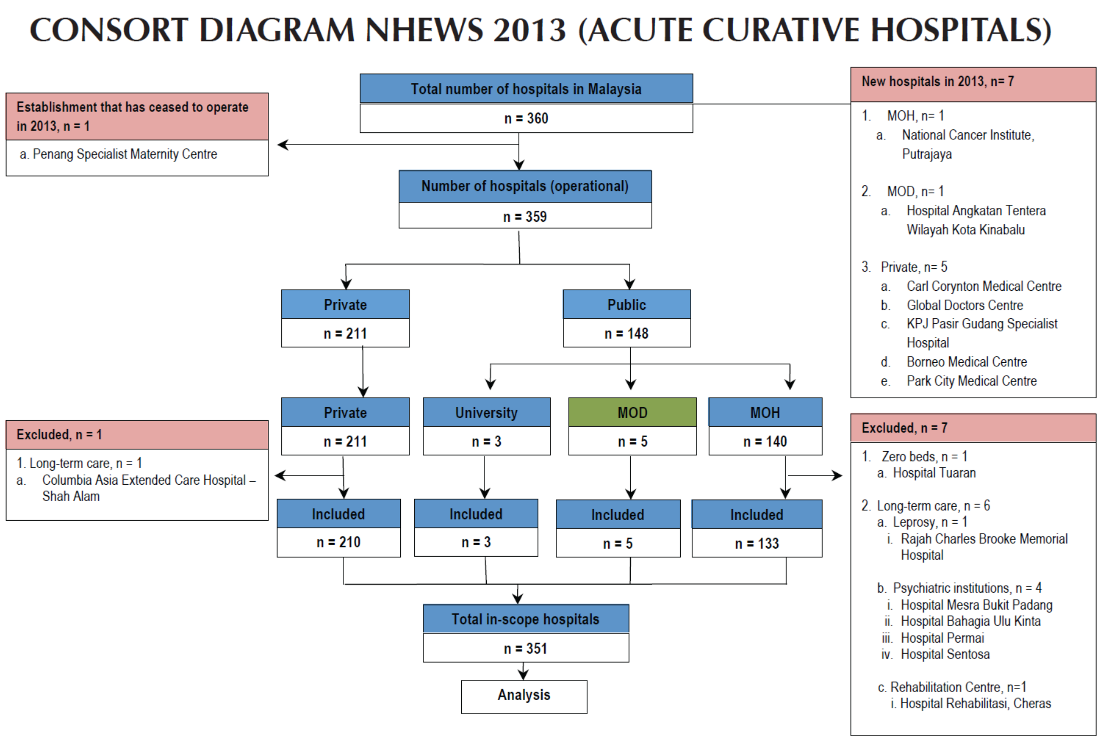
Respondents had the option between two modes of data collection and submission:

1. Paper data submission via hard copy case report forms (printed CRF)
2. Electronic data submission via National Healthcare Statistics Initiative web application electronic case report forms (eCRF)

Data collection for the workforce section, particularly for the doctor workforce involved relevant details (e.g. qualification and specialty) of each doctor working in the hospital. Datasets containing the list of doctors for each hospital, which was obtained from its participation in the past NHEWS (Hospital) surveys, were pre-uploaded to the eCRFs of 2013. This aimed at minimizing the need for manual data entry of the current survey. In comparison, data obtained for the remaining workforce category involved only the total count of the workforce.

Data from paper submissions were screened manually and reviewed for their completeness and logical consistency before data entry into the NHEWS (Hospital) database by trained members. Data submissions through electronic CRFs were entered directly into the NHEWS (Hospital) database by the data providers. Quality of data entry was inspected and maintained by several built-in features such as a compulsory data checking, consistency checks, auto-calculations and auto-default data from the previous NHEWS (Hospital) surveys. Activities performed in the database were recorded by an audit trail system.

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

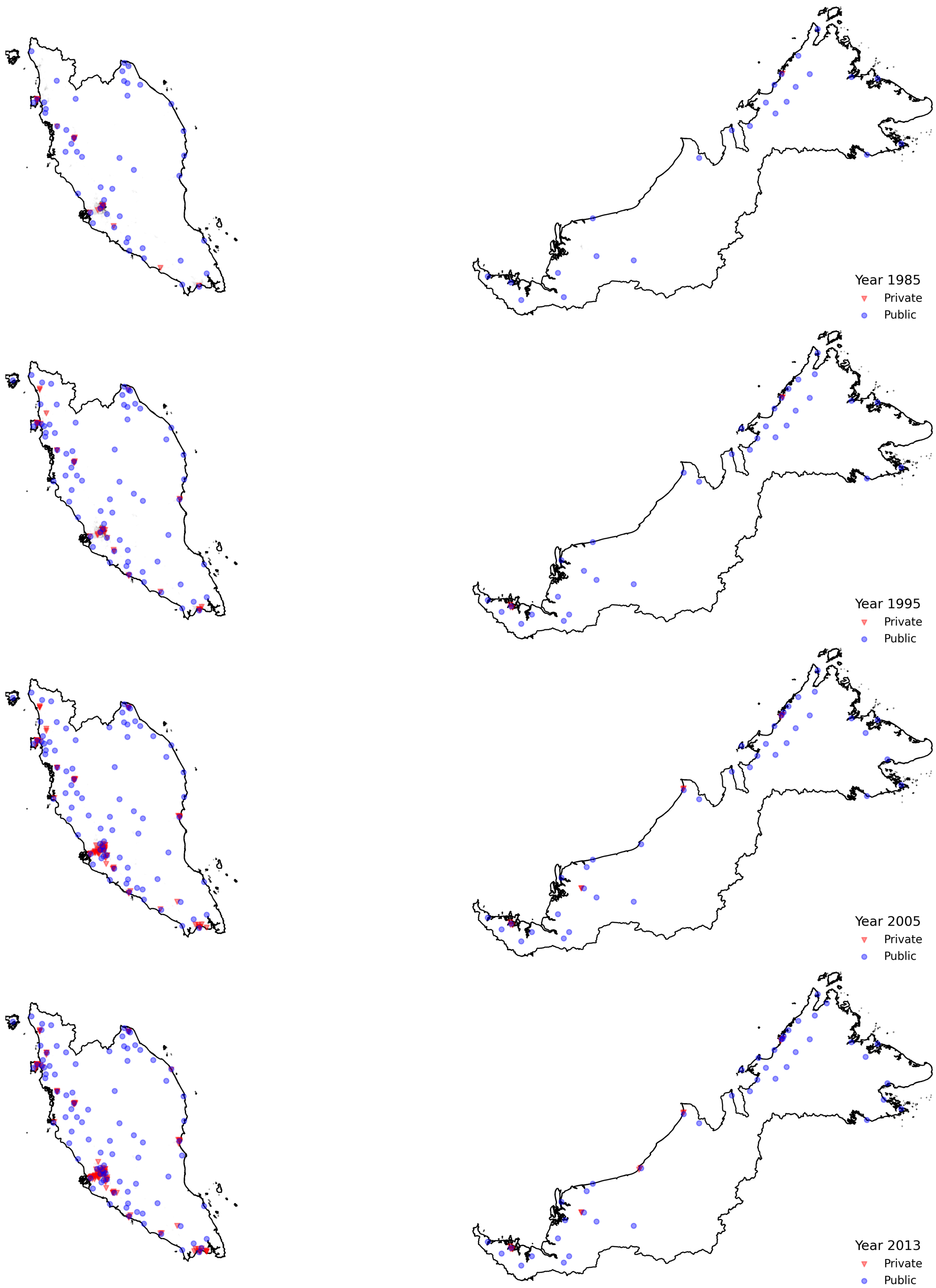
Table A.1: Summary Statistics

	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)

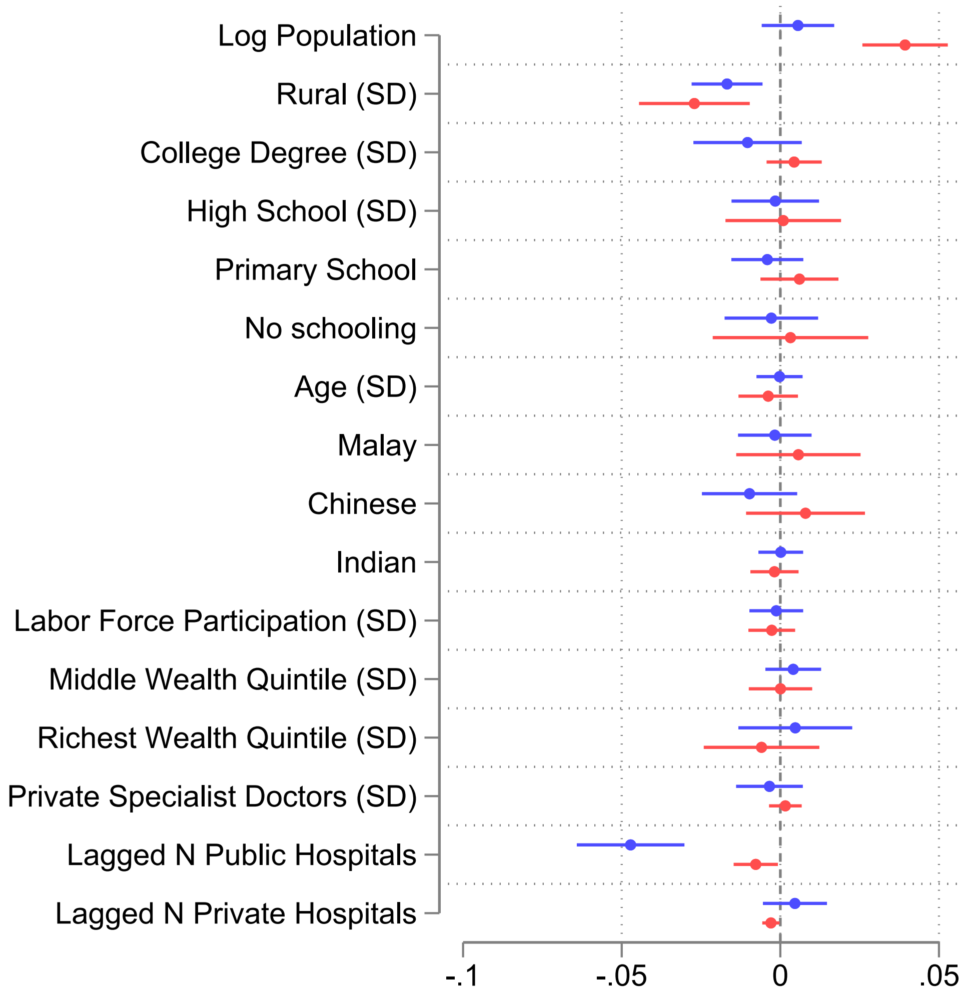


Note: Data on hospital locations are from the National Healthcare Establishment Workforce Survey (2013). This figure shows the locations of public and private hospitals in Malaysia from 1982 to 2013.

Figure A.4: Example Hospital Images

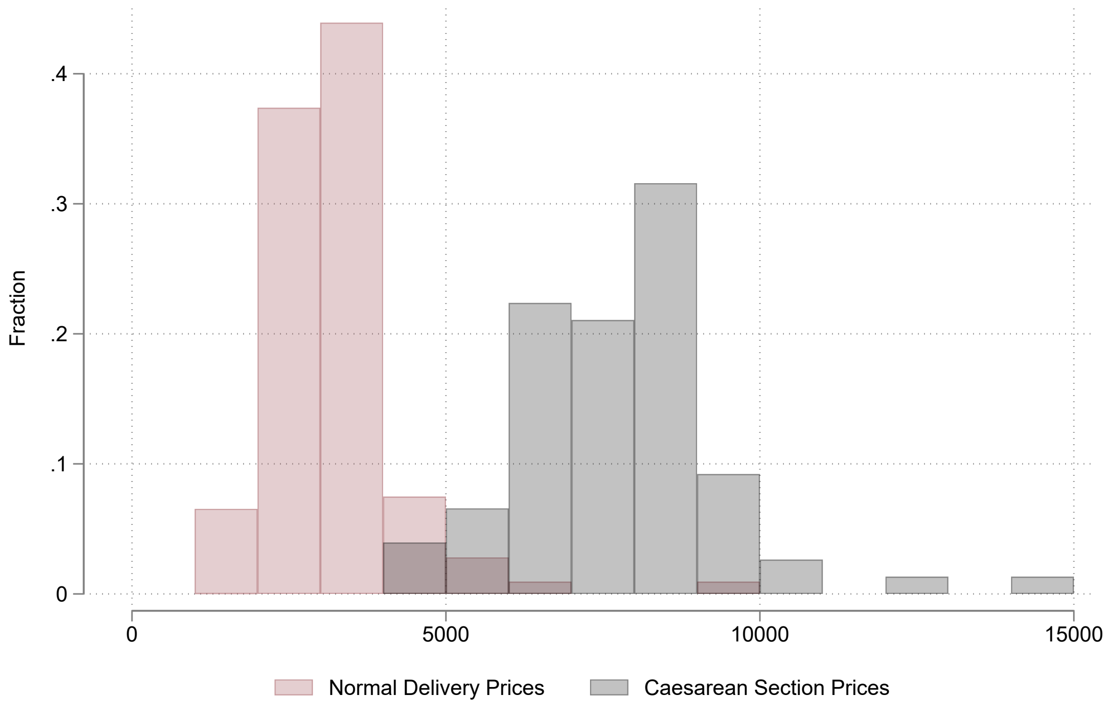
Note: These panels show examples of what hospitals in Malaysia look like based on their categories.

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



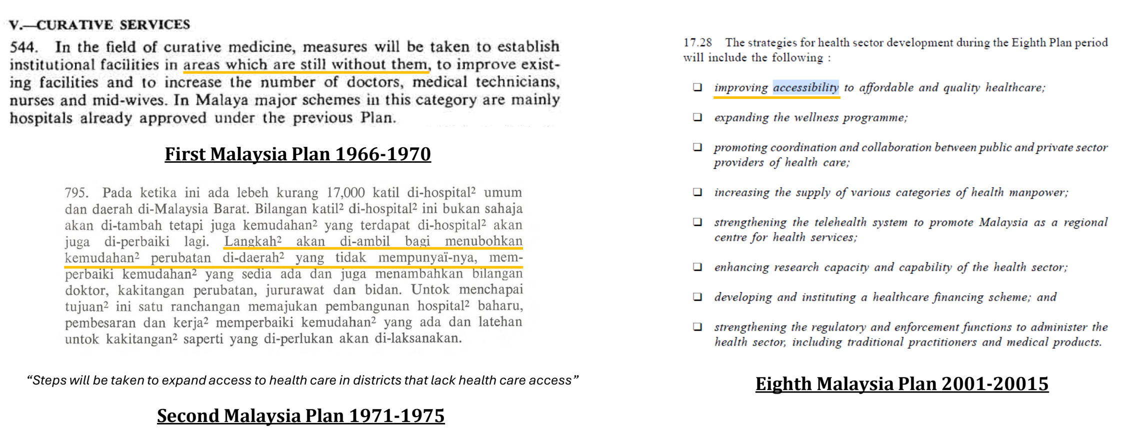
Note: These coefficients are average marginal effects from logit regressions with year fixed effects of public (or private) hospital entry on a set of district characteristics.

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 mempunyai-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

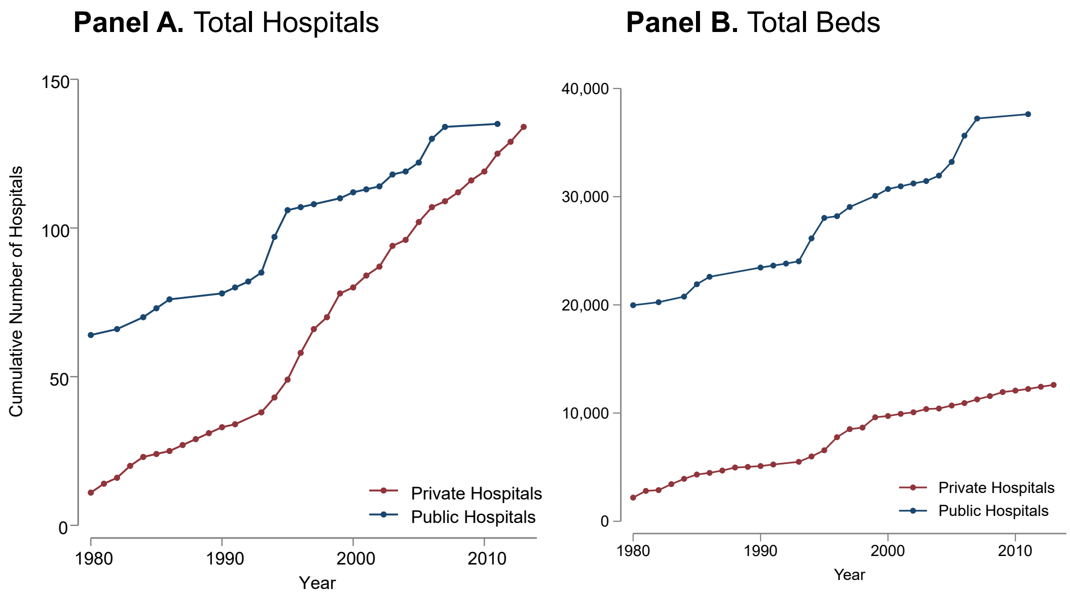
17.28 The strategies for health sector development during the Eighth Plan period will include the following :

- *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

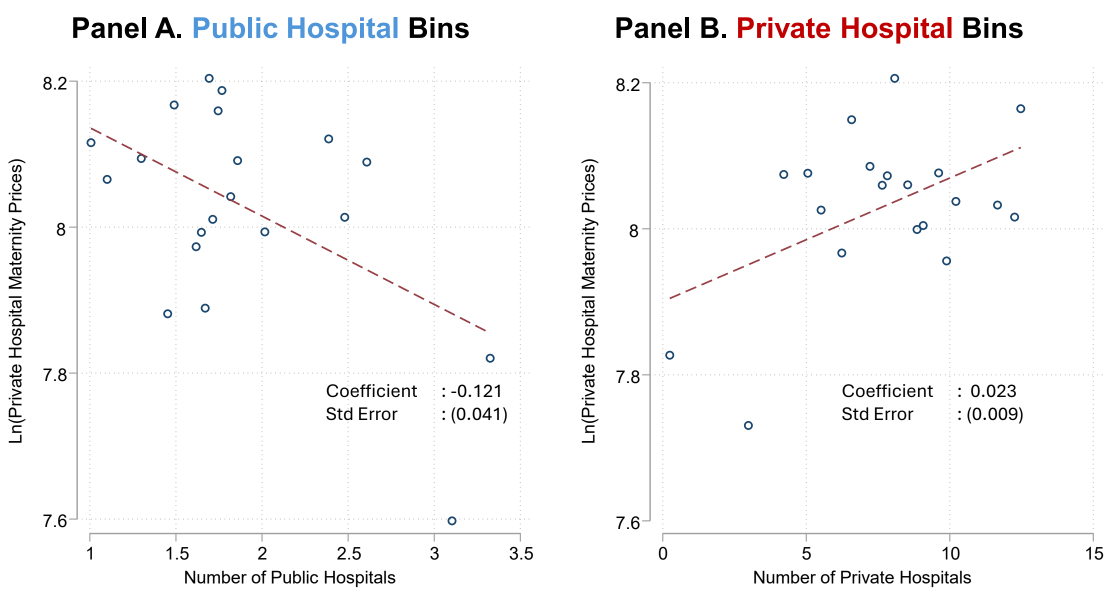
Note: These excerpts are taken from various planning documents related to healthcare development in Malaysia. These panels show the commitment of the Malaysian government in prioritizing access to healthcare.

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



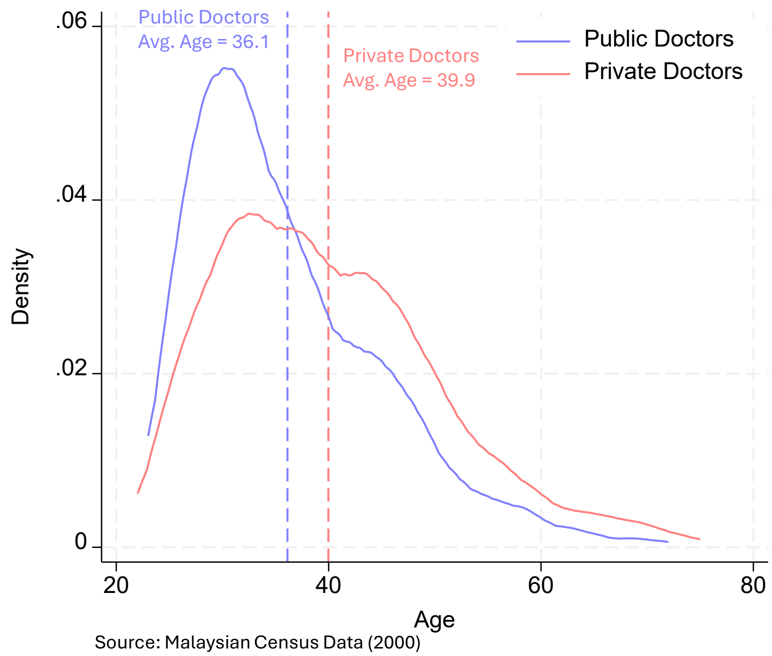
Note: This figure shows the total count of hospitals and the number of beds available in public and private hospitals in Malaysia between 1980 and 2014.

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



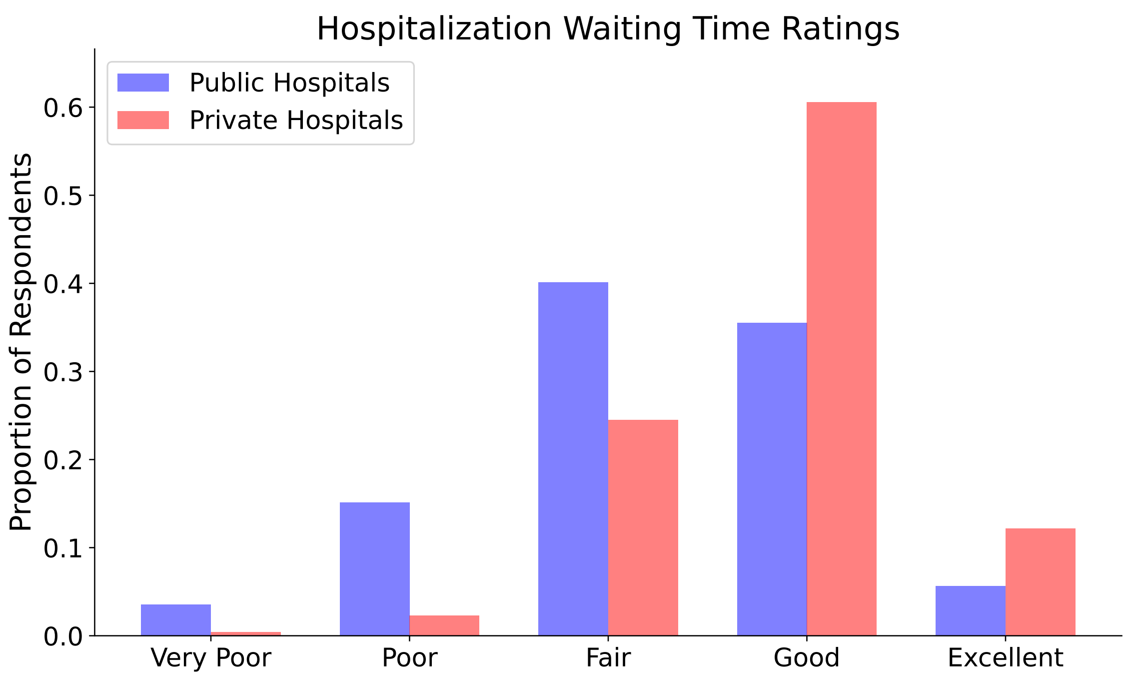
Note: Panel A figure shows a binscatter of private hospital normal delivery prices against the number of public hospitals within the same district. Panel B shows a binscatter against the number of private hospitals within the same district. This figure shows descriptive evidence on public competitive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

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



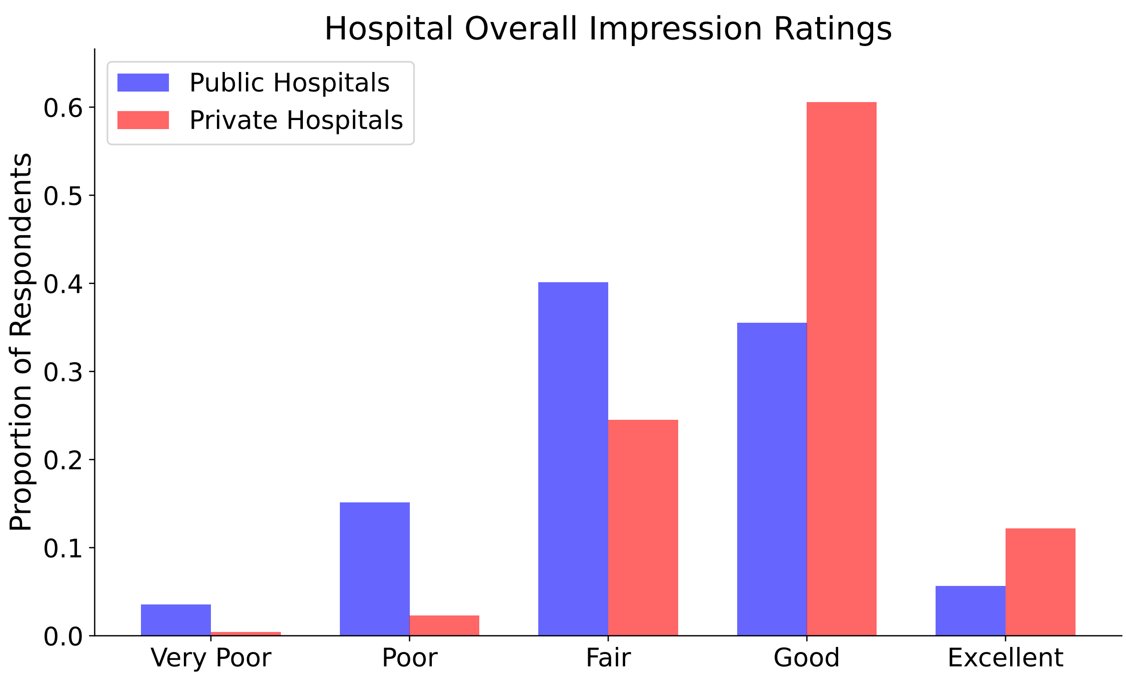
Note: This figure shows the average age of physicians working in public and private hospitals in Malaysia. The difference is approximately 3.8 years. This roughly coincides with the two-year compulsory public housemanship period in the public sector.

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

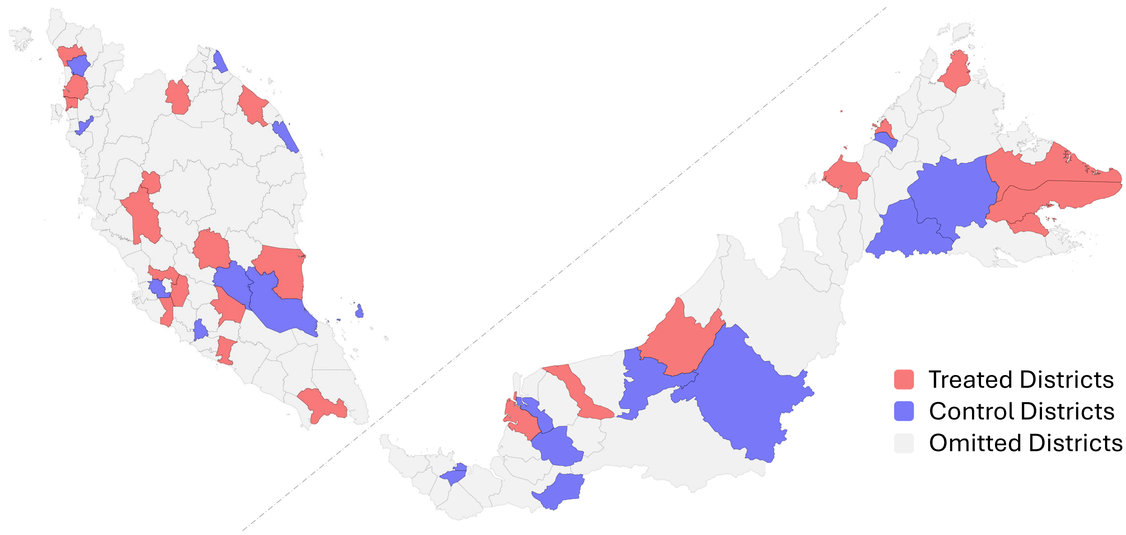


Note: This figure shows survey respondents' overall ratings of public and private hospitals in Malaysia from the National Health and Morbidity Survey 2015.

B Further Details on Reduced Form

B.1 Additional Tables and Figures

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: 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. Main results (Table 4) use lag 0. The lag represents the number of years between hospital construction and when effects are measured. Effects for specialist hospitals strengthen at longer lags, consistent with residency training programs requiring several years to graduate specialists who then enter private practice. Coefficients represent the effect of each additional public hospital on the number of private specialist physicians (in units of 100s). Panel A shows effects of specialist public hospitals; Panel B shows effects of non-specialist public hospitals. The stacked design compares districts treated in 1970-1980 vs. never-treated (Stack 1) and districts treated in 1980-1991 vs. never-treated (Stack 2), using 1970, 1980, and 1991 census data. All specifications include district-by-stack and year-by-stack fixed effects. Standard errors clustered at the district level are in parentheses. Mean dependent variable is calculated across all observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure B.2: Proportion of Outpatient, Emergency and Inpatient Visits at Private and Public Hospitals

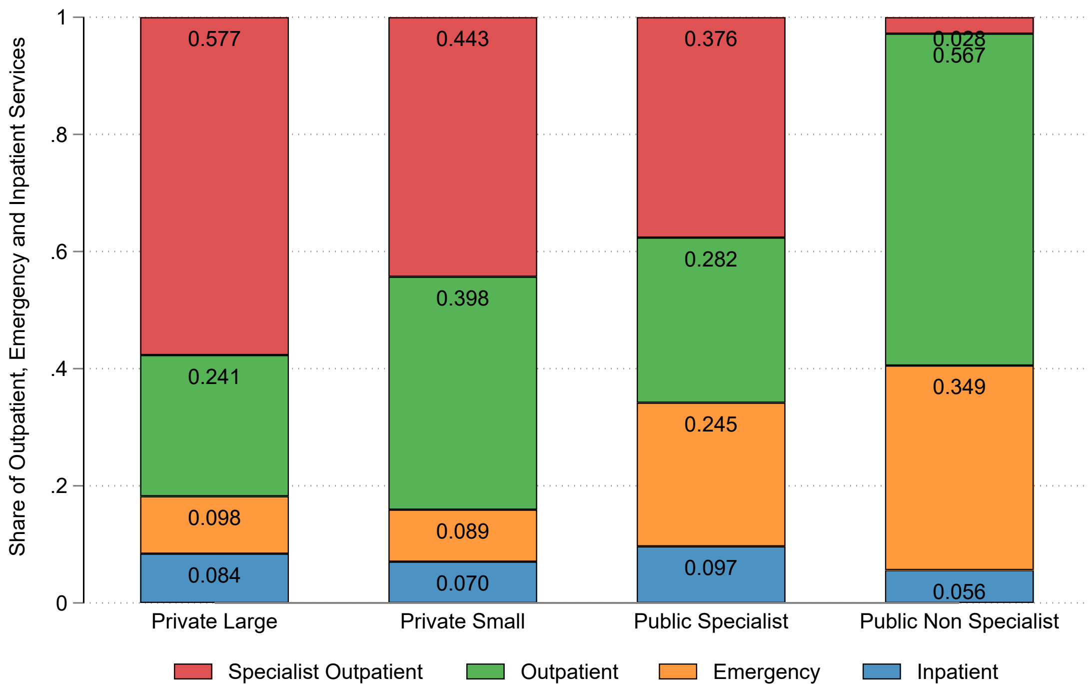
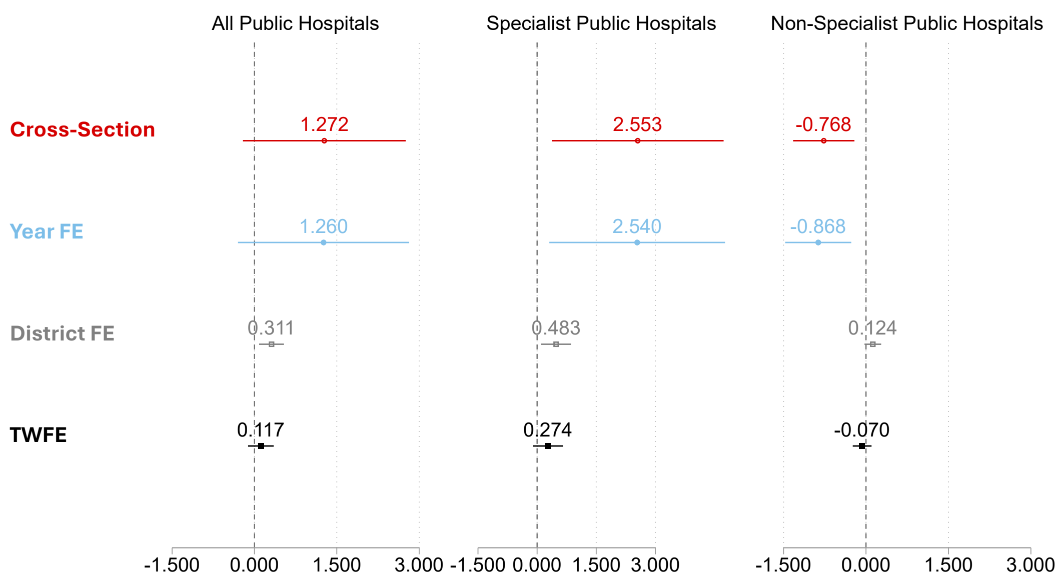


Figure B.3: Balancing Regressions



Notes: This figure shows the results of the balancing regressions. I first predict the number of private hospital using district-level characteristics in Table 1. I then estimate the specification denoted on the y-axis using this predicted outcome as the dependent variable. 'Cross-Section' refers to the estimation Equation 6 but without any fixed effects, and leads and lags replaced by one post $\times$ treat variable. 'Year FE' and 'District FE' add year and district fixed effects, respectively. 'TWFE' includes both sets of fixed effects. The x-axis shows the coefficient on the treatment indicator, with 95% confidence intervals.

Table B.2: Dynamic Effects of Public Hospital Construction

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 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 (SDID) estimator (Arkhangelsky et al., 2021). This method addresses potential confounding by constructing synthetic control units that optimally weight both untreated districts and pre-treatment time periods to better match the treated units' characteristics and trends.

Table B.3 presents the average treatment effects using the SDID estimator. The results closely mirror the main findings from the event study analysis. All types of public hospitals increase private hospital entry by 0.406 hospitals on average (which is similar compared to 0.465 in the main specification). When disaggregating by hospital type, specialist public hospitals generate a positive and significant effect of 0.692 additional private hospitals (again, similar compared to 0.785 in the main results), while non-specialist public hospitals show a small and statistically insignificant negative effect of -0.016 hospitals.

Figure B.4 shows the dynamic treatment effects over time using the SDID estimation strategy. Panel A shows that the positive effect of all public hospitals increases gradually, becoming statistically significant around year 3 and growing to approximately 0.5 additional private hospitals by year 7. Panel B shows that specialist public hospitals drive this pattern, with effects beginning in year 2 and reaching nearly 1 additional private hospital by the end of the observation period. Panel C in contrast, shows that non-specialist public hospitals have negligible effects throughout the post-treatment period, with confidence intervals consistently encompassing zero.

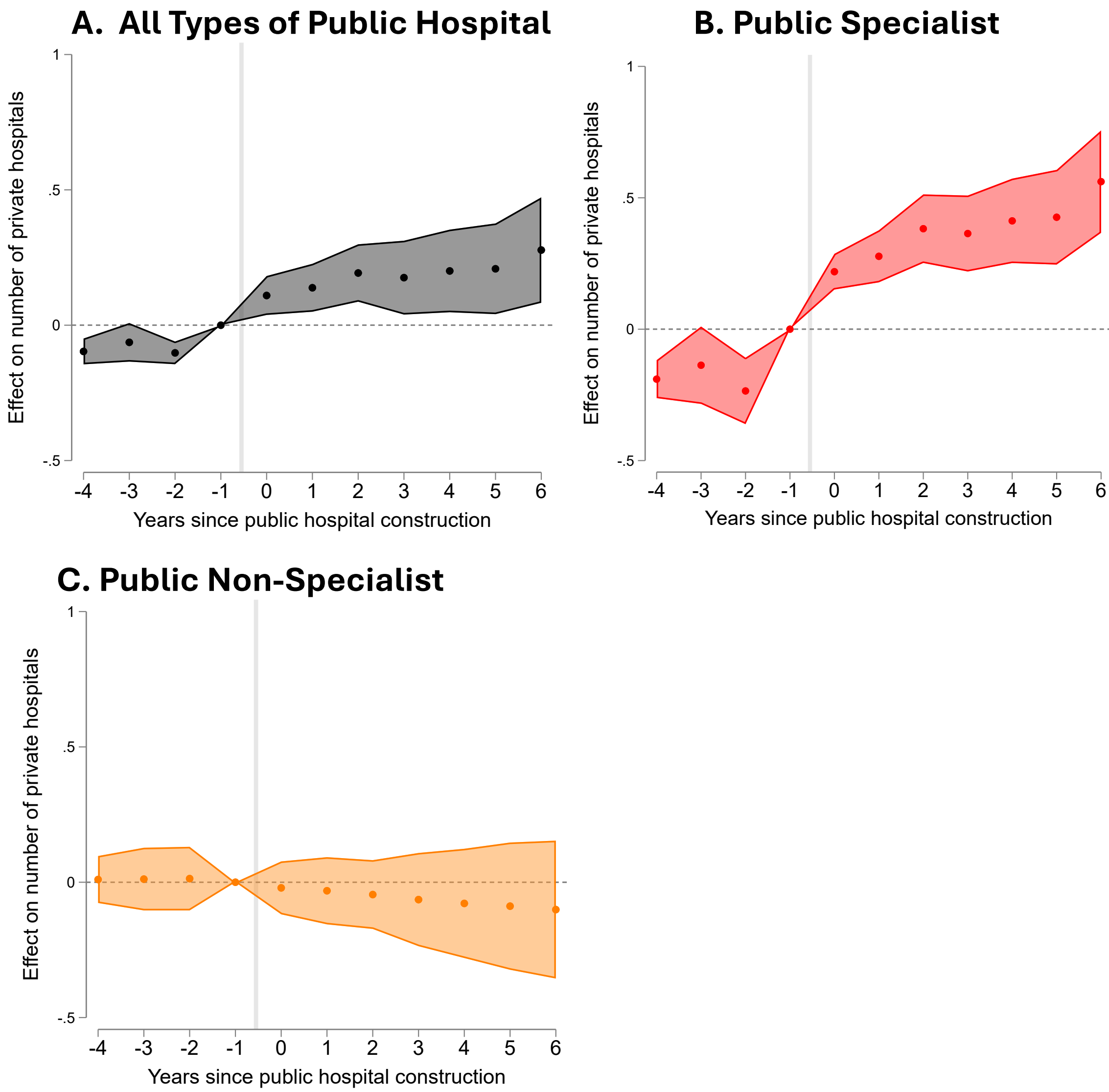
Overall, the similarities in findings between the main event study results and these SDID estimates provides strong evidence that the findings are robust to concerns about pre-treatment differences between treatment and control districts

Table B.3: Average Treatment Effects on Private Entrants - Synthetic Difference-in-Differences

	Count of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	0.406**		
	(0.168)		
E2: Specialist public hospitals		0.692**	
		(0.275)	
E3: 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Each column presents results using the Synthetic DiD estimator (Arkhangelsky et al., 2021). SEs in parentheses.

Figure B.4: Synthetic Difference-in-Differences: Dynamic Treatment Effects



Note: Panel A plots the dynamic treatment effects from Arkhangelsky et al. (2021) with all types of public hospitals as treatment units. Panel B are for specialist public hospitals while Panel C is for non-specialist public hospitals. The control units are selected using the Synthetic DiD procedure. The shaded area represents the 95% confidence interval.

B.3 Matching

To further address concerns about pre-treatment imbalances, I use coarsened exact matching (CEM) to balance treatment and control districts on key observable characteristics that showed the largest imbalances in the raw data: rurality and the number of existing public hospitals in 1996. The matching procedure reduces the sample from a total of 47 districts (25 treatment, 22 control) to 28 districts (12 treated, 16 control).

Table B.4 shows that matching removes all statistically significant differences between treatment and control groups. Most notably, the previously significant differences in population size (p=0.037) and rurality (p=0.063) are no longer present.

Figure B.5 presents the event study results using the matched sample. The average post-treatment effect is 0.108 additional private hospitals, representing a 31.4 percent increase relative to the pre-treatment mean of 0.344 hospitals in the matched sample. This is similar to the main specification, which showed a 47.5 percent increase (0.465 relative to a mean of 0.979).

I focus this robustness check on all types of public hospitals rather than disaggregating by hospital type because the sample reduction is substantial. Splitting the already-small matched sample by treatment type would yield insufficient variation for reliable inference, particularly given that specialist public hospitals represent only a subset of the 12 remaining treated districts.

Figure B.5: Event Study of Matching on Private Hospital Entrants

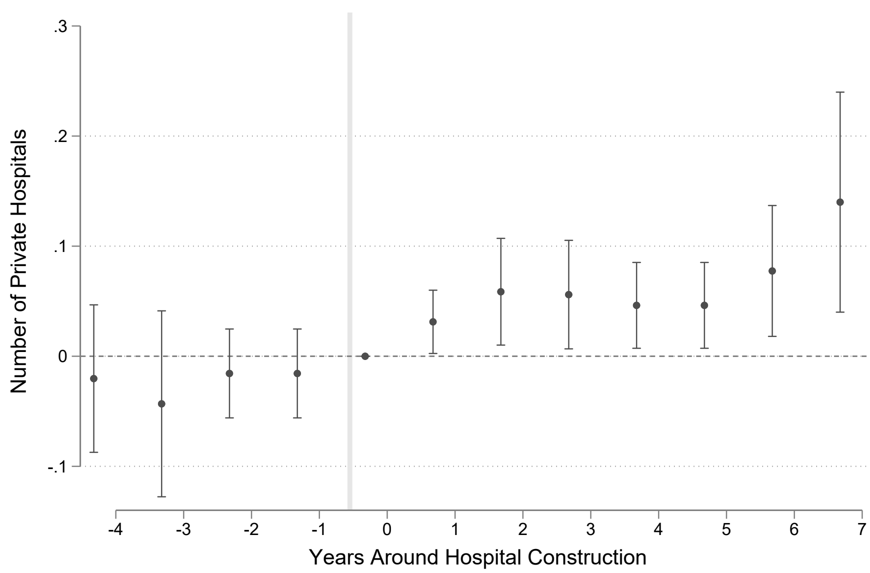


Table B.4: Post-Matching Summary Statistics by Treatment Status

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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.4 Additional Robustness Checks

Table B.5: Main Effects Robustness: Dropping Multiple Treated Districts

	Count of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	0.457***		
	(0.151)		
E2: Specialist public hospitals		0.937***	
		(0.114)	
E3: Non-specialist public hospitals			-0.171***
			(0.009)
Mean Outcome	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
Unique Events	22	11	11
Estimator	SA	SA	SA

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Each column presents results from separate regressions using the Sun and Abraham (2021) estimator. Standard errors in parentheses clustered at the district level.

Table B.6: Main Effects Robustness: Last-Treated as Control

	Count of Private Hospitals		
	(1)	(2)	(3)
E1: All public hospitals	0.684***		
	(0.081)		
E2: Specialist public hospitals		0.599***	
		(0.088)	
E3: Non-specialist public hospitals			—
Mean Outcome	0.979	1.278	—
District Fixed Effects	Yes	Yes	—
Year Fixed Effects	Yes	Yes	—
N Districts × Year	.	.	—
R^2	0.980	0.975	—
Unique Events	25	14	—
Estimator	SA	SA	—

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Columns (1) and (2) show results using last-treated districts as controls. Column (3) is not estimated because both last-treated control districts and non-specialist treated districts had zero private hospital entrants, providing no variation for identification. SEs in parentheses clustered at district level.

Table B.7: 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Each column presents post-treatment average effects using different estimators for staggered DiD designs.

C Further Details on Model and Estimation

C.1 Demand 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 private hospital j is operated by firm f, where firms are either the government or private entrepreneurship groups. I treat public hospitals as having an exogenously fixed price at MYR 100. 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 Type I Extreme Value 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 8, 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 8 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 $\gamma_i \text{distance}_{ij}$, 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.

I model choice probabilities following the mixed logit form $s_{ijd} = \frac{\exp(V_{ijd})}{1+\sum_{k \in J_d} \exp(V_{ikd})}$, with aggregate market shares 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.

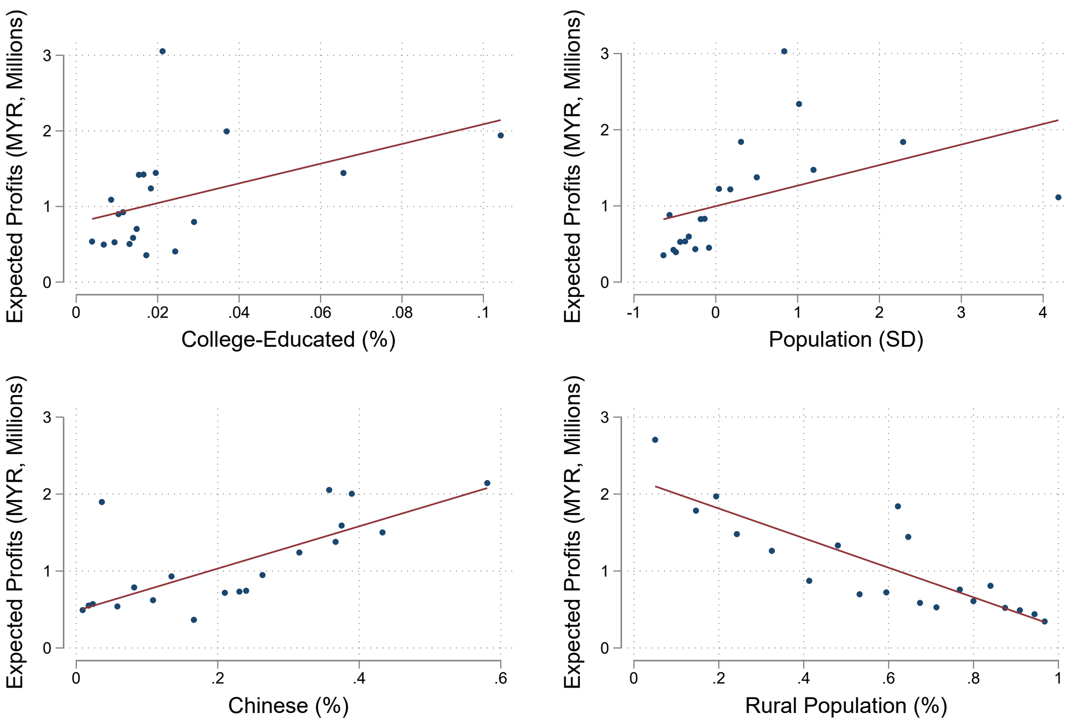
I estimate the model by GMM, minimizing the objective function $\min_\theta q(\theta) = \bar{g}(\theta)' W \bar{g}(\theta)$, where θ includes the non-concentrated parameters Σ and Π, and $\bar{g}(\theta)$ contains both demand-side moments $\bar{g}_D = \frac{1}{N} \sum_{j,d} Z'_{D,jd} \xi_{jd}$ and the 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.

I tabulate the demand estimates in Table C.1 and the fitted micro moments in Table C.2. 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. The results show strong income-based heterogeneity in price sensitivity. 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

Figure C.1: 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.

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. These estimates suggest that private hospital entry would be most profitable in high-income districts, where consumers demonstrate both ability to pay higher prices and willingness to choose between private options based on price and quality characteristics.

Table C.1: Demand Estimates Across Specifications

	Specification			
	OLS Logit (1)	IV Logit (2)	Random Coeffs (no micro) (3)	Rand. Coeffs Microdata (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. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$. 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.2: 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.

Table C.3: 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. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$. 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.

C.2 First-Stage CCP and Transition Estimates

C.3 CCP of Private Entry

Table C.4 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.

Table C.4: 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–Q5, baseline Q2), counts of public specialist and non-specialist hospitals, incumbent private hospitals, and log population. Marginal effects are average partial effects on $\Pr(\text{Entry})$. For factor levels, dy/dx is the discrete change from Q2. Standard errors are clustered by district.

C.4 Additional Tables and Figures on Model and Estimation

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

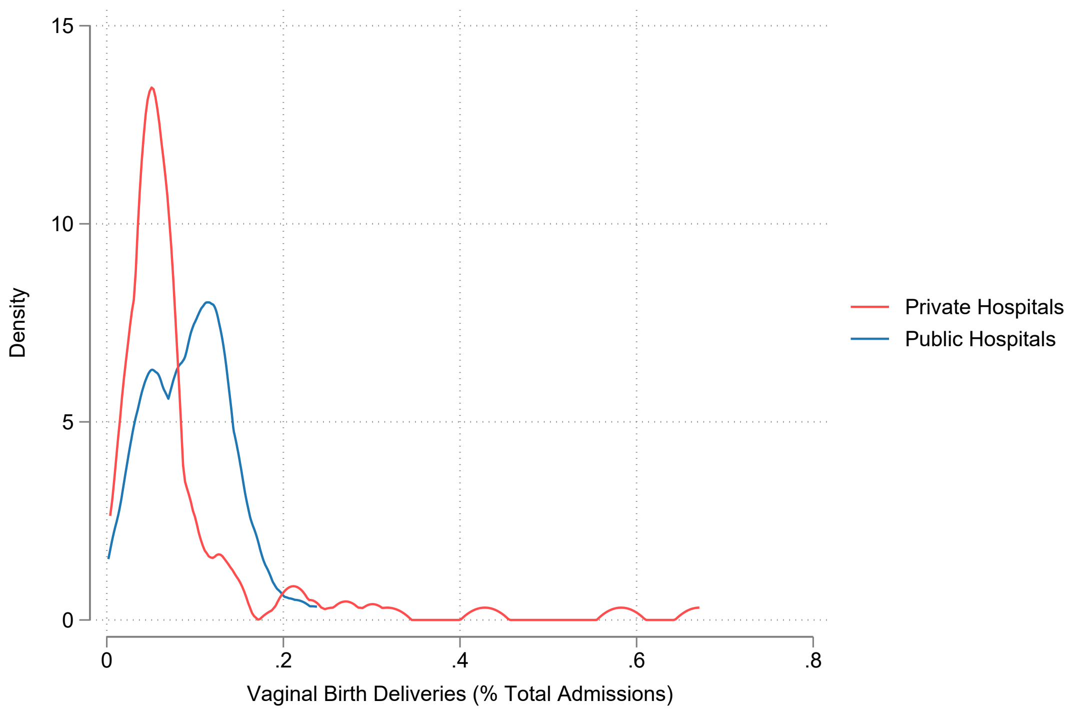
Notes: This table lists the top diagnoses in private hospitals with their corresponding ICD-10 codes, descriptions, patient counts, and percentages of total diagnoses.

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.2: Birth Share Density

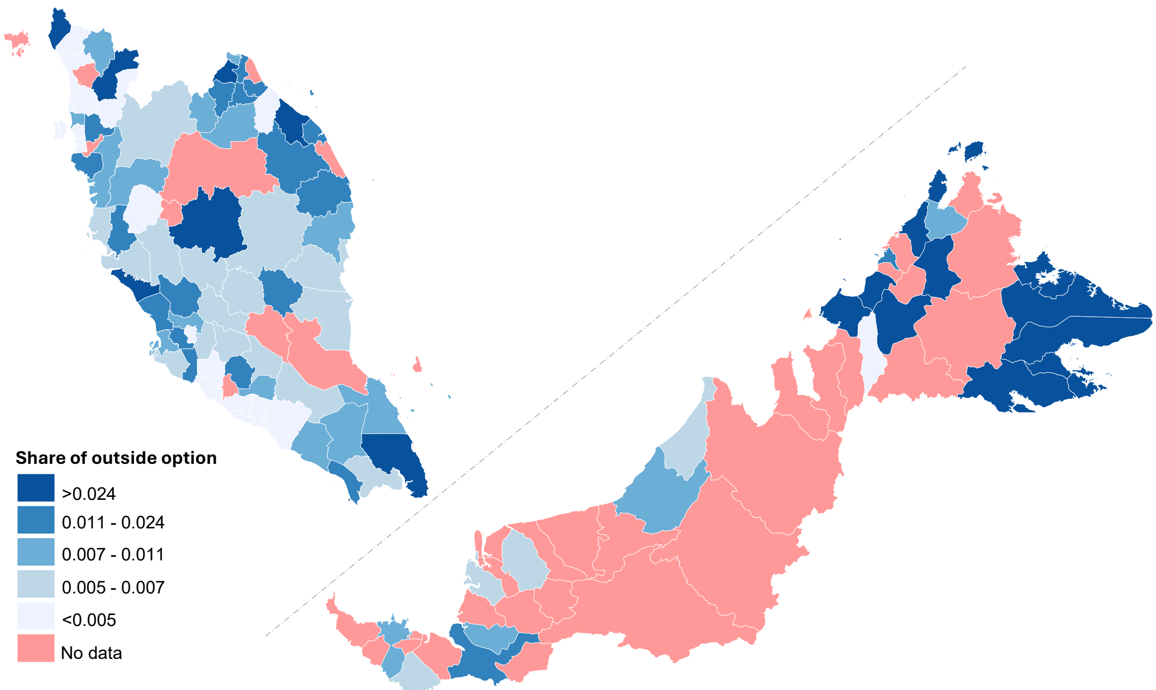


Notes: This figure shows the density of birth shares across public and private hospitals in Malaysia.

Figure C.3: Selected Maternity Package Posters

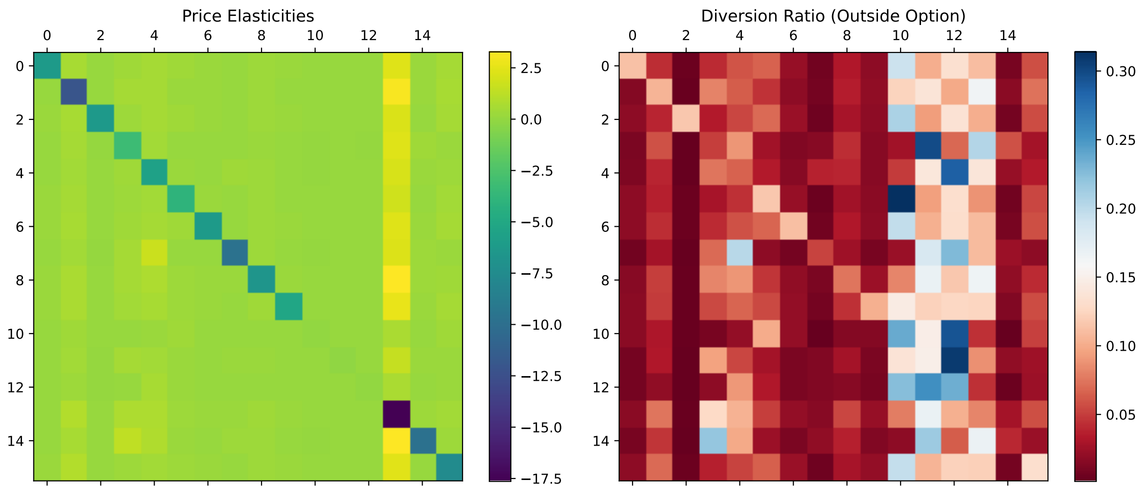
Notes: These posters advertise the maternity packages offered by private hospitals in Malaysia. The packages typically include prenatal care, delivery services (normal or C-section), postnatal care, and sometimes additional services such as ultrasounds or newborn care. Prices vary based on the hospital's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

Figure C.4: 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.5: Estimated Price Elasticities and Diversion Ratios for the Kuala Lumpur District



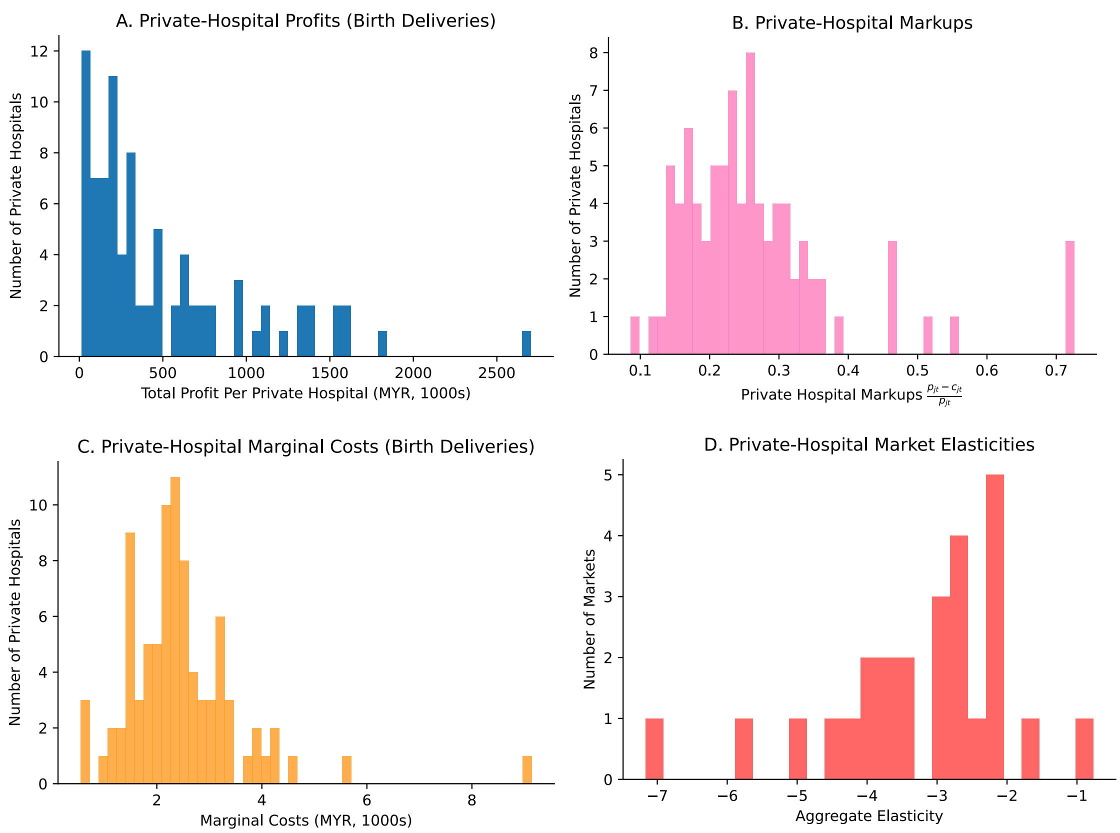
Notes: Price elasticities $\varepsilon_{jk} = \frac{\partial s_k}{\partial p_j}\frac{p_j}{s_k}$ measure the percentage change in market share of product k in response to a one percent change in the price of product j. Own-price elasticities (diagonal elements) are negative, while cross-price elasticities (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.

Table C.7: Entry Cost Estimates (MYR Millions) with Varying Profit Expectations

	Baseline ($\lambda = 0$)		**Optimistic** ($\lambda = 0.1$)		**Pessimistic** ($\lambda = -0.1$)	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Private doctors (1996)	−0.022	−0.024	−0.025	−0.027	−0.020	−0.022
	(0.010)	(0.012)	(0.011)	(0.014)	(0.009)	(0.011)
Ln population	1.764	1.895	2.039	2.176	1.619	1.730
	(1.218)	(1.262)	(1.382)	(1.436)	(1.108)	(1.149)
Ln land price	2.846	2.870	3.105	3.129	2.500	2.520
	(2.018)	(2.040)	(2.284)	(2.309)	(1.825)	(1.845)
Observations	94	94	94	94	94	94
R^2	0.075	0.075	0.075	0.075	0.074	0.073
First-stage F		5.0		5.0		5.0
Implied effect of specialist public hospital:						
Mean entry cost (million RM)	6.32		7.02		5.72	
Cost reduction (million RM)	1.20	1.31	1.37	1.48	1.09	1.20
As % of mean cost	19.0%	20.8%	19.5%	21.0%	19.1%	21.0%

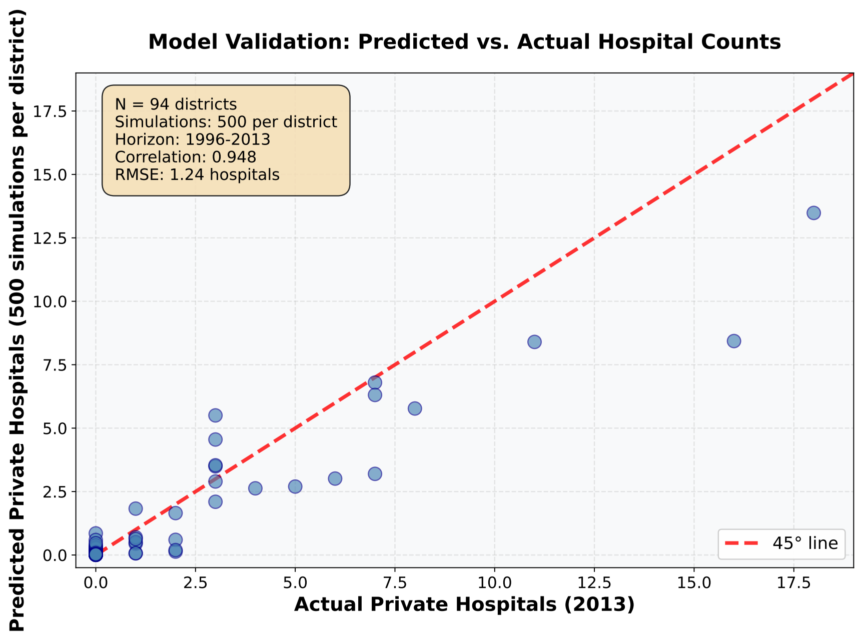
Notes: Dependent variable is the revealed entry cost κ_{dt} in millions of MYR. Columns vary λ, which adjusts expected profit levels: $\mathbb{E}[\pi_{d,1996}] = \bar{\pi}^{SW}_{d,1996}(1+\lambda)$. Standard errors clustered at district level in parentheses. IV specification instruments 1996 specialist physicians with 1980 data. Mean entry cost computed from dependent variable. Cost reduction equals $-(\gamma_3) \times 54.7$ million MYR, where 54.7 is the specialist hospital effect on physician supply from Table 4.

Figure C.6: 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.7: 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.

D Counterfactual Details

The reduced-form findings show that specialist and non-specialist public hospitals have opposing effects on private entry. To quantify the welfare implications of these findings, I conduct counterfactual simulations that compare the effects of building additional public hospitals of each type. This section details the counterfactual exercise.

D.1 Overview

The counterfactual exercises simulate the effects of adding one public hospital to each district that did not historically receive one between 1997 and 2013. I conduct two separate counterfactuals of adding a specialist hospital and adding a non-specialist hospital. For each counterfactual experiment, I compare between a baseline scenario where we fix the historical allocation of public hospitals and a treatment scenario where we add one additional public hospital to the district in post-1996. I run this procedure for each district that does not have a hospital of the relevant type in 1996. I then simulate the market equilibrium forward from a 1996 baseline through 2013, allowing private hospitals to enter in response to the public hospital intervention. I then compare private entry counts, private prices, private market shares and welfare between the baseline (historical allocation) and treatment (historical allocation plus one additional public hospital) scenarios.

The simulation proceeds in three stages. First, I initialize the market structure using observed hospital characteristics in 1996. Second, I simulate forward year-by-year from 1997 to 2013, determining private entry using conditional choice probabilities from the BBL estimation combined with moments from the event studies. Third, I solve for the Bertrand-Nash pricing equilibrium in each year conditional on market structure and compute welfare. I repeat this procedure for each eligible district and each hospital type.

D.2 Baseline Market Structure

The counterfactual baseline uses the observed market structure in 1996, prior to the public hospital construction program. The 1996 baseline contains 148 hospitals across 95 districts: 88 public hospitals (47 specialist, 41 non-specialist) and 41 private hospitals. I exclude districts where data limitations prevent estimation of either demand parameters or entry costs. For each hospital, I observe beds, staffing levels, specialty indicators, ownership structure, and the unobserved quality component ξ_j recovered from BLP estimation. Public hospitals are priced at the regulated rate of 100 MYR for normal deliveries, while private hospital prices are determined in equilibrium. Market size is measured by total births per district, which I project forward using observed population growth rates.

D.3 New Hospital Characteristics

When adding a new public hospital to a district, I must specify its characteristics. I construct hospital templates using median characteristics from existing hospitals of each type observed in the 1996 data. The specialist hospital template has 504 beds, while the non-specialist template has 90 beds. Both templates are priced at the regulated rate of 100 MYR. Construction cost ratios are set at 5.4:1 for specialist hospitals to non-specialist hospitals, based on Ministry of Health reports on budget allocations during the study period. For unobserved quality ξ_j, I assign the median ξ from existing hospitals of the same type within the same district when available, or the national median for that hospital type otherwise. This approach ensures that new hospitals have characteristics representative of their type rather than extreme values.

D.4 Private Hospital Entry

Private entry in each year combines two components. The first consists of the baseline entry probability from the first-step BBL estimation and event study moments from public hospital construction. The BBL estimation recovers conditional choice probabilities (CCPs) that map market states to entry probabilities. The state space includes the number of existing private hospitals, public specialist hospitals, public non-specialist hospitals, private specialist physicians, and log population. For each district-year, I look up the CCP corresponding to the current state to obtain the baseline probability of entry.

When a public hospital exists in a district, the event study coefficients modify private entry. Let τ denote years since the public hospital opened. The induced private entry from a specialist hospital of age τ is given by:

$$\lambda_{\tau}^{S} = \sum_{s=0}^{\tau} \hat{\beta}_s^S \tag{23}$$

where $\hat{\beta}_s^S$ are the event study coefficients from Table B.2. The analogous expression holds for non-specialist hospitals using coefficients $\hat{\beta}_s^{NS}$. Total private entry probability in district d at time t combines the baseline CCP with event study effects:

$$\Lambda_{dt} = \text{CCP}(\mathbf{s}_{dt}) + \sum_{j \in \mathcal{J}_d^{pub}} \lambda_{\tau_j}^{type(j)} \tag{24}$$

where $\mathbf{s}_{dt}$ is the state vector, $\mathcal{J}_d^{pub}$ is the set of public hospitals in district d, and τ_j is the age of hospital j. The number of entering private hospitals is drawn from a Poisson distribution with parameter Λ_{dt}. New private hospitals receive characteristics from a private hospital template constructed analogously to the public templates. I assign unobserved quality ξ using the median from existing private hospitals in the district. Under counterfactual public hospital allocations, I update all state transitions including physician supply.

D.5 Pricing Equilibrium

Conditional on market structure in each year, private hospitals compete in prices while public hospital prices remain fixed at 100 MYR. I solve for Bertrand-Nash equilibrium prices using an iterative best-response algorithm.Private hospital j owned by firm f sets prices to maximize profits:

$$\max_{p_j} \sum_{k \in \mathcal{J}_f} (p_k - mc_k) \cdot s_k(\mathbf{p}) \cdot M_d \tag{25}$$

where $\mathcal{J}_f$ is the set of hospitals owned by firm f, $s_k(\mathbf{p})$ is the market share of hospital k given the price vector, and M_d is total births in district d. The first-order conditions yield:

$$s_j + \sum_{k \in \mathcal{J}_f} (p_k - mc_k) \frac{\partial s_k}{\partial p_j} = 0 \tag{26}$$

In matrix form, for all private hospitals:

$$\mathbf{s} + (\mathbf{O} \odot \mathbf{\Omega})(\mathbf{p} - \mathbf{mc}) = 0 \tag{27}$$

where $\mathbf{O}$ is the ownership matrix with $O_{jk} = 1$ if hospitals j and k belong to the same firm, and $\mathbf{\Omega}$ is the Jacobian of shares with respect to prices. I solve for equilibrium prices iteratively:

1. Initialize prices at observed values (baseline) or previous year's equilibrium (forward simulation).
2. Compute utilities V_{ij}, shares s_j, and Jacobian Ω_{jk} given current prices.
3. Update private prices: $\mathbf{p}^* = \mathbf{mc} - (\mathbf{O} \odot \mathbf{\Omega})^{-1}\mathbf{s}$
4. Apply damping: $\mathbf{p}^{new} = (1 - \alpha)\mathbf{p}^{old} + \alpha \mathbf{p}^*$ with $\alpha = 0.3$.
5. Repeat until FOC residuals fall below 10^{-4} or maximum iterations reached.

Convergence typically occurs within 50 iterations. I impose a price floor of 10 MYR to prevent numerical issues from near-zero prices. The ownership matrix $\mathbf{O}$ reflects multi-product firm internalization of pricing externalities. Hospital chains (KPJ, Pantai, Columbia Asia, Sime Darby) own multiple hospitals and internalize substitution between their facilities. Solo entrepreneurship hospitals are single-product firms with $O_{jj} = 1$ and $O_{jk} = 0$ for $j \neq k$. Public hospitals do not engage in price competition and have zero entries in the ownership matrix.

D.6 Capacity Constraints and Rationing

Hospitals face physical capacity constraints that may prevent them from serving all patients who would choose them in an unconstrained equilibrium. I model this through a rationing parameter $\lambda_j \in [0, 1]$ that captures the probability a patient can be served at their chosen hospital.

Capacity Calculation. For each hospital j, annual birth capacity depends on beds, length of stay, and the fraction of total admissions that are maternity cases:

$$\text{Capacity}_j = \frac{\text{Beds}_j \times 365}{\text{LOS}_j} \times \text{BirthShare}_j \tag{28}$$

where LOS_j is the average length of stay in days and BirthShare_j is the proportion of total inpatient admissions that are obstetric cases. When hospital-specific length of stay data is unavailable, I use type-specific defaults: 1.71 days for public hospitals and 7.70 days for private hospitals, reflecting the shorter stays typical at subsidized public facilities. The birthshare is computed from observed admissions data when available, with a default of 15 percent otherwise.

Rationing Mechanism. Given market shares s_j from the demand model and total district births M_d, demand for hospital j is $D_j = s_j \times M_d$. The rationing parameter is:

$$\lambda_j = \min\left(1, \frac{\text{Capacity}_j}{D_j}\right) \tag{29}$$

When $\lambda_j < 1$, the hospital is capacity-constrained: only a fraction λ_j of patients who choose hospital j can be served. Rationed patients receive the outside option (home birth or traditional birth attendant), which is normalized to zero utility. Importantly, rationed patients are not reassigned to their second-choice hospital—this simplification avoids the computational complexity of iterating over reassignment cascades while capturing the primary welfare cost of capacity constraints.

Rationing in Equilibrium. Capacity constraints do not enter the utility function directly; consumers choose hospitals based on price, distance, and quality without observing current congestion levels. This assumption reflects the institutional setting where patients typically make hospital choices during prenatal care, before knowing realized congestion at the time of delivery. The rationing parameter λ_j applies mechanically after choices are made, reducing effective market shares:

$$\tilde{s}_j = s_j \times \lambda_j \tag{30}$$

This creates an indirect welfare effect: capacity-constrained hospitals generate lower consumer surplus because some patients who would have received positive utility from hospital care instead receive the outside option.

Empirical Relevance. In the 1996 baseline, capacity constraints bind primarily for maternity centers and smaller private hospitals rather than for public specialist hospitals. Public specialist hospitals, despite exhibiting 73.9 percent bed occupancy rates in the descriptive statistics, have sufficient beds (504 on average) that the obstetric ward rarely reaches capacity for deliveries alone. The model allows capacity constraints to bind endogenously as counterfactual allocations change the distribution of demand across hospitals.

D.7 Simulation Procedure

I summarize the simulation procedure for each district-treatment pair as:

I run the baseline simulation (historical allocation only) and treatment simulation (historical allocation plus one additional hospital) for each district. The welfare effect of adding a hospital to district d is:

$$\Delta W_d = W_d^{treatment} - W_d^{baseline} \tag{31}$$

Algorithm 1: Counterfactual Simulation

Input: District d, hospital type $\in$ {specialist, non-specialist}
Initialize: Load 1996 baseline market structure
Treatment: Add new public hospital to district d in 1997
for year $t = 1997$ to 2013 **do**
    Compute private entry probability Λ_{dt}
    Draw number of entrants $\sim$ Poisson(Λ_{dt})
    Add entering private hospitals with template characteristics
    Solve Bertrand-Nash pricing equilibrium
    Compute market shares and welfare
end for
Output: Welfare in 2013, hospital counts, market shares

D.8 Handling Equilibrium Failures

In some district-year combinations, the pricing equilibrium solver fails to converge or produces economically implausible results (prices below marginal cost). These failures typically occur when intense competition drives prices toward the floor, creating numerical instability. I address this in two ways. First, I impose a price floor of 10 MYR and cap markups at marginal cost to ensure positive margins. When the unconstrained equilibrium implies $p_j < mc_j$ for private hospital j, I set the margin to zero: $p_j = mc_j$. Second, I exclude districts with persistent equilibrium failures from the main analysis. Two districts (Timur Laut and Kuala Lumpur) exhibit equilibrium issues in the baseline simulation and are excluded from reported results. Both districts have unusually high numbers of private hospitals (8 and 15 respectively) creating intense competition.

D.9 Identification and Limitations

The counterfactual analysis relies on several maintained assumptions. First, I assume the demand parameters estimated from 2013 cross-sectional variation are stable over the 1997–2013 simulation period. Second, the entry model assumes private hospitals have rational expectations about the public hospital construction schedule and make entry decisions based on expected future profits. Third, I assume new hospitals have characteristics drawn from the observed distribution of existing hospitals rather than optimally chosen. These assumptions may be violated if consumer preferences, entry costs, or hospital quality changed substantially during the study period. However, the relative comparison between specialist and non-specialist effects should be robust to level changes that affect both hospital types similarly.